Aus dem
EpiCentre, Institute of Veterinary and Animal Biomedical Sciences, Massey University,
Palmerston North, Neuseeland

Vorgelegt über die
Klinik für Wiederkäuer mit Ambulanz und Bestandsbetreuung
der Ludwig-Maximilians-Universität München
(Vorstände: Prof. Dr. W. Klee, Prof. Dr. H. Zerbe)

Arbeit angefertigt unter der Leitung von Prof. Dr. R. Mansfeld

Factors associated with grower herd performance in three New Zealand pig farms

Inaugural-Dissertation
zur Erlangung der tiermedizinischen Doktorwürde
der Tierärztlichen Fakultät der Ludwig-Maximilian-Universität
München

von
Birgit Schauer
aus Regensburg
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This thesis is dedicated to my family for their great understanding and continuous support.

Abstract

The aim of this observational study was to identify performance parameters, which can be used to predict market weight of a batch of pigs on commercial farms. For that purpose, we obtained weekly retro- and prospective production records from three New Zealand pig farms. The observation periods on farms A, B, and C were 140, 127 and 90 weeks, respectively. As we expected the data to be autocorrelated, we used two modelling approaches for multivariable analysis: An autoregressive (AR) model and an ordinary least squares (OLS) regression model ('naive approach'). Analyses were performed separately for each farm. Using an AR-model, we identified four production parameters (weaning age, two sample weights and days to market) across the three farms that were effective in predicting market weight with accuracies greater than 70%. All AR-models yielded stationary and normally distributed residuals. In contrast, residuals of the OLS-models showed remaining autocorrelation on farms B and C indicating biased model estimates. Using an AR-model also has the advantage that immediate future observations can be forecasted. This is particularly useful as all predictor variables (apart from 'Days to market') could be obtained a month prior to marketing on all farms.

Kurzfassung

Die Zielsetzung dieser Beobachtungsstudie war es, Leistungsparameter zu identifizieren, die es ermöglichen das Vermarktungsgewicht von Schweinegruppen auf kommerziellen Schweinefarmen vorherzusagen. Für diesen Zweck haben wir sowohl retro- als auch prospektive Produktionsdaten von drei neuseeländischen Schweinefarmen erhoben. Die Beobachtungszeiträume auf den Farmen A, B und C erstreckten sich über 140, 127 und 90 Wochen. Da wir Autokorrelation in den Daten vermuteten, benutzten wir zwei Modellierungsansätze: Ein autoregressives (AR) Model und ein Ordinary Least Squares (OLS) Regressionsmodel (‚naives Model'). Wir entwickelten ein separates Model für jede einzelne Farm. Mit Hilfe des AR-Models konnten wir vier Produktionsparameter (‚Absetzalter', zwei Gewichtsmessungen und ‚Tage bis zur Schlachtung') identifizieren, die das Schlachtgewicht auf allen drei Farmen mit mehr als 70% Genauigkeit vorhersagen. Alle AR-Modelle produzierten stationäre und normalverteilte Residuen. Im Gegensatz dazu, Residuen der OLS-Modelle zeigten verbleibende Autokorrelation für die Farmen B und C, was auf verfälschte Modelschätzungen schliessen lässt. Die Anwendung eines AR-Models hat zudem den Vorteil dass unmittelbar zukünftige Beobachtungen vorhergesagt werden können. Dies ist vor allem hilfreich da alle unabhängigen Variablen (abgesehen von ‚Tage bis zur Schlachtung') auf jeder Farm ein Monat vor der Schlachtung erhoben werden können.

Nomenclature

AIAO	All-in/All-out production system
ACF	Autocorrelation function
AR	autoregressive term (lag specified by subsequent number); autoregressive process
ARMA	autoregressive moving-average process
CI	confidence interval
CV	coefficient of variation (%)
d	day(s)
DF	degrees of freedom
DTM	days to market
DW	Durbin-Watson statistics to test for autocorrelation
IQR	interquartile range
kg	kilogram(s)
LM-test	Lagrange multiplier test for heteroscedasticity
MA	moving average process
n	number or sample size
OR	odds ratio
p	order of the autoregressive process
P	P-value
PACF	Partial autocorrelation function
Q-test	Portmanteau Q-Test for heteroscedasticity
r	correlation coefficient
R^2	squared correlation, R-squared value
SD	standard deviation
SE	standard error
SRL	special rearing location
WEEK	study week
WGT	Sample weight

Table of Contents

Table of Figures

Table of Tables

Chapter 1 Introduction

Modern pig farming is a highly intensive farming system with various options to manipulate nutrition, environment and health. Furthermore, the pigs' potential has increased through genetic improvement, which has altered the pigs' nutrient requirements over the years. Concurrently, producers are confronted with difficulties such as depression in pork price, regulations of food safety and the impact of disease. Under these circumstances, continuous cost-effective optimisation of performance is essential for the survival of the pig unit. Monitoring grower herd performance will gain in importance in this area, both as a tool for problem detection and for decision-making. The grower herd is of particular interest because this is the production unit where most of the money is made or lost.

It has been stressed by several authors that optimisation of production efficiency depends upon accurate performance assessment (Brumm 1995; Polson et al. 1998). Performance assessment includes data collection, data quality control, data analysis and correct interpretation of results. This presents a challenging task and is probably one of the reasons why a well-functioning performance monitoring system is often not present on commercial farms (Losinger 1998a; Deen et al. 2002).

Knowledge about which variables are useful to collect allows shifting the effort away from collecting the data towards enhancing data quality, analysing and interpreting the data and responding to the obtained information in a timely manner (action-taking). Several studies have been published of how to collect feed intake and growth curve data (De Lange et al. 1997; Dritz et al. 1997a; Caldwell 1998; Dritz et al. 1998; Goodband 2001) and how to apply growth models on commercial farms (Schinckel et al. 1996; Schinckel et al. 2002). However, little research is available investigating what routinely collected data are useful as indicators for overall growth performance. Hence, the goal of this observational study was to identify performance parameters, which can be used to predict market weight of a batch of pigs on three commercial farms in New Zealand. We also aimed to describe mean values as well as temporal fluctuations in measured predictor variables on the three investigated farms. Based on this knowledge, we intended to develop recommendations regarding which parameters are important to collect on commercial farms and what techniques can be applied to facilitate an effective monitoring system.

Chapter 2 Literature review

2.1 Profiling the New Zealand pig industry

2.1.1 Pig industry in New Zealand and other major pig producing countries

New Zealand has a small pig industry compared to other countries. For instance, Germany produces approximately 100 times as much pig meat as New Zealand (Table 2.1.1). Currently, about 14,000 pigs are slaughtered every week in New Zealand at a mean carcass weight of 67 kg, which is low compared to pig carcass weights in Germany (95 kg). This is primarily driven by the demand of New Zealand packer companies. Furthermore, boars are not castrated in New Zealand, so that boar taint is an additional barrier to grow boars to heavier carcass weights. Economically, low slaughter weights adversely affect the international competitiveness of the New Zealand pig industry since the production cost per kg of meat is higher when producing smaller pigs (Meyer 2000; Kim, Y. S. et al. 2005).

Table 2.1.1. Pork production volume and mean pig carcass weight in New Zealand and other pig producing countries.

Country	Annual production of carcass weight (1000 t)	Mean carcass weight (kg)
New Zealand	46 [a]	67 [d]
Germany	4, 500 [b]	95 [e]
Australia	420 [c]	73 [f]
USA	9, 402 [c]	88 [f]
Canada	1, 960 [c]	85 [f]

a: Source: Statistics New Zealand (2003).
b: Source: ZMP (2006).
c. Source: Campbell (2006).
d: Source: New Zealand Pork Industry Board (2006): Average for 2005.
e. Source: Bayerische Landesanstalt für Landwirtschaft (2005).
f. Source: Australian Government Productivity Commission (2005).

Profitability of pig production is highly affected by changes in feed and pig prices. Figure 2.1.1 illustrates the development and forecasts of New Zealand and world prices for wheat and barley between 2002 and 2007. Feed prices tended to decline since 2003, and forecasts predict that feed prices remain low. However, the New Zealand feed price per ton of wheat and barley is approximately 30 to 50 Euros higher than the world feed price.

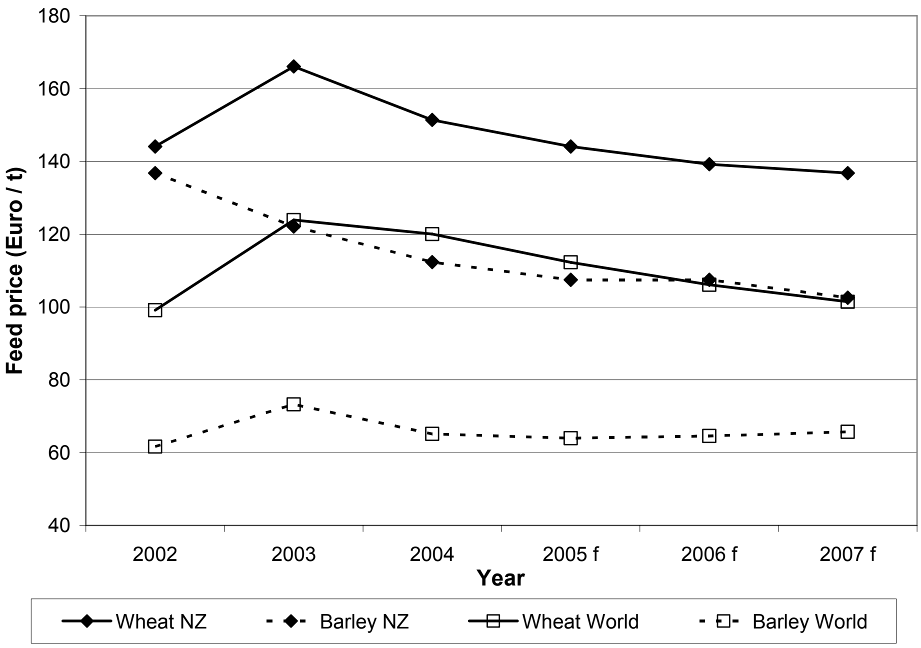

Figure 2.1.1. New Zealand (NZ) and world prices for wheat and barley for the years 2002 to 2007. Values for 2005 to 2007 are based on forecasts (f). Source: MAF (2004). New Zealand dollars were converted to Euros using a conversion factor of 0.4885 (http://www.x-rates.com, 2 June 2006).

According to the Australian Government Productivity Commission (2005), world pig prices declined from mid 2001 until the end of 2003 and increased in the first half of 2004. In contrast, New Zealand pig prices remained relatively stable since mid 2003 fluctuating between 1.40 and 1.60 Euros per kg carcass weight (head-on) (New Zealand Pork Industry Board 2006).

The New Zealand payment system for pig meat is based on a classification grid including weight and back fat measurements. An optical probe is used to measure P2-back fat at a point 65 mm off the midline of the back at the last rib. The payment grid of many processors penalizes overfat carcasses (generally P2-back fat greater than 12 mm) and overweight carcasses resulting in a small window for optimum marketing weight. Therefore, some farms weigh pigs individually pre-market to optimise their marketing returns.

2.1.2 Pig production within New Zealand

In New Zealand, pork is mainly produced for the domestic market. A small export market exists, which targets especially the Singapore market besides Taiwan, South Korea and Japan (New Zealand Pork Industry Board 2004b). Domestic production decreased by 12% between 1995 and 2000 and remained relatively stable thereafter (Figure 2.1.2). On the contrary, imported pork (mostly in frozen form) constantly increased over this period, contributing 36% to the domestic market in New Zealand in 2002/2003 (New Zealand Pork Industry Board 2003). Imported pork came predominantly from Australia (49%), Canada (38%) and the USA (8%).

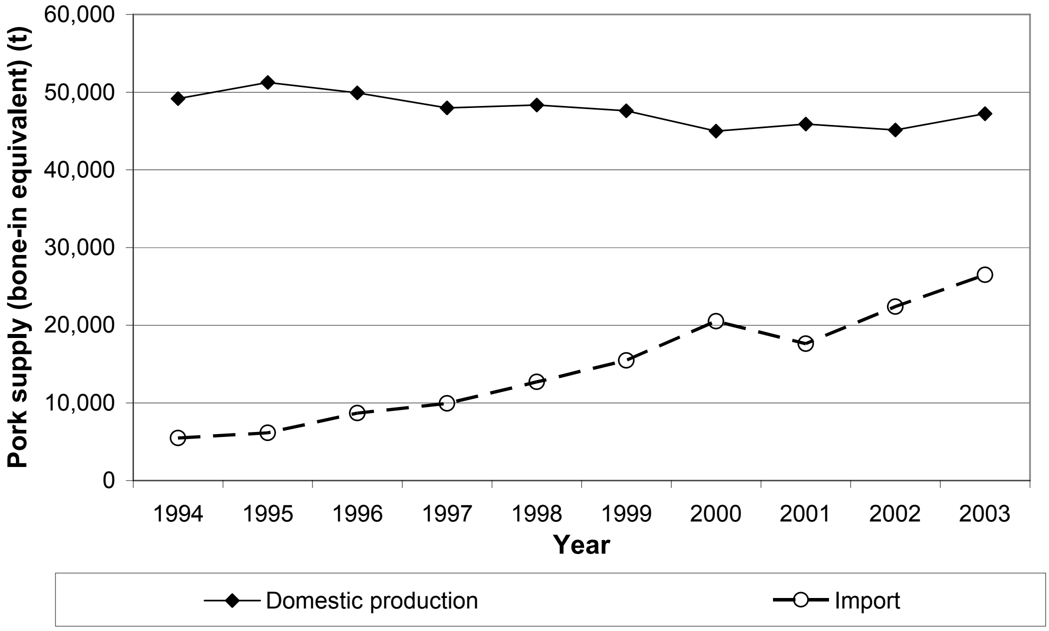

Figure 2.1.2. Pork supply to New Zealand from domestic production and imports. Source: New Zealand Pork Industry Board (2003).

2.1.2.1 Location, herd size, type of herds

New Zealand lies southeast of Australia, and stretches between 34 and 48 degrees of latitude on the Southern hemisphere (Figure 2.1.3a). Thus, the climate ranges from a warm subtropical climate in the far north to a cool temperate climate in the far south. Mean annual temperatures range from 10°C in the south to 16°C in the north. In contrast to the Northern hemisphere, the months December to February present the summer months and June to August are the winter months.

Figure 2.1.3. (a) Geographical position of New Zealand in relation to Australia (small map) and (b) map of New Zealand with the North and the South Island.

Main pig production areas in New Zealand are found south of Auckland and north of Christchurch (Figure 2.1.3b). There are approximately 42,000 breeding sows in New Zealand (Statistics New Zealand 2003). An older survey showed that 86% of the sows were kept on 250 farms with herd sizes greater than 100 sows (Statistics New Zealand 2000). One third of these 250 farms was located in the North Island.

A strong divergence exists between pig production in the North and the South Island: The North Island has three times as many residents as the South Island, whereas the main grain producing areas are located in the South Island. This leads to differences in the type of production system used as well as in feed and pork prices. Commercial pigs in the North Island are almost exclusively farmed indoors, whilst in the South Island they are often raised outdoors. Feed and straw prices are generally lower in the South Island, whereas carcass revenues are higher in the North Island due to the closer proximity to consumers.

2.1.2.2 Genetics

Commercial pigs are derived from female breeding stock supplied to the commercial farms by breeding companies. These sows are generally Large White x Landrace crosses. Terminal sires are meat line boars, generally Duroc or Duroc crossed with Landrace or Large White. Artificial insemination has replaced natural mating in large parts in the indoor units over the last three years while it is only starting to be established recently in outdoor units.

Import of genetic material from overseas is restricted to minimise the risk of introducing new diseases. Semen may only be imported from premises in Australia, USA, New Caledonia and Norway if these meet the Import Health standards. Live pigs from Australia and New Caledonia may also be imported under the provision of a permit in conjunction with a quarantine period for at least 30 days.

2.1.2.3 Disease

Due to its isolated geographical position and strict import regulation, New Zealand has been isolated from the following diseases (New Zealand Pork Industry Board 2004a):

- African Swine Fever
- Atrophic rhinitis (viral)
- Aujezsky disease virus
- Classical Swine Fever
- Hog cholera virus
- Menangle disease
- Porcine Reproductive Respiratory Syndrome (PRRS)
- Swine influenza
- Swine vesicular disease

Post-weaning Multisystemic Wasting Syndrome (PMWS) was first diagnosed in a small cluster of small-holder pig units near Auckland (North Island) in September 2003 (Stone 2004). No further cases were detected until January 2006 despite intense nationwide surveillance of nearly 180 farms. In January 2006, a second cluster of infected farms was found near Christchurch (South Island), which could not be linked to the North Island outbreak and is considered to be a new incursion of PMWS into New Zealand (McIntyre et al. 2006). After the South Island outbreak, eradication of the disease was not considered feasible anymore. First, the infected South Island farms are larger commercial farms, including outdoor units. Secondly, when the disease was diagnosed, it has already spread through weaner pig networks in contrast to the North Island outbreak (McIntyre et al. 2006).

The prevalence of endemic pig diseases at slaughter was investigated in a survey between 1986 and 1990 on 2762 carcasses from 46 pig herds (Christensen et al. 1990). The pig prevalence was 45% for enzootic pneumonia, 13% for ascariasis and 13% for clinical mange. Histological investigation of thickened lesions of the terminal ileum suggested a pig prevalence of Porcine Intestinal Adenomatosis (PIA) of 0.8%. The prevalence of enzootic pneumonia and gastric ulcers was significantly greater in large-sized herds (≥ 250 sows) than in small- (50 to 119 sows) or medium-sized herds (120 to 249 sows). In contrast, prevalence of mange and ascariasis was significantly lower in medium- and large-sized than in small-sized herds.

2.1.2.4 Feeding

With increasing specialization, grain-based diets have widely replaced by-product feeding. Grain typically makes up 80% of the pig feed. Main grain sources are barley and wheat in the South Island, and barley and maize in the North Island (New Zealand Pork Industry Board 2004c).

By-product feeders still exist particularly around larger cities feeding bread, milk, cheese or other food industry by-products. Economically, feeding by-products reduces feed cost, but is generally related to reduced growth performance (Spinelli et al. 2000).

2.1.2.5 Housing

Pigs are farmed indoors and outdoors in New Zealand. Light free-draining soil, lower cereal and straw prices and mild temperatures in summer provide good conditions for outdoor production on the South Island, where outdoor production is predominantly found. A survey of housing systems on 76 New Zealand pig farms (Gregory et al. 1999) reported that during the dry sow period the majority of farms (57%) housed sows in stalls compared to a small percentage of farms housing sows in pens (18%) and paddocks. However, under the upcoming Animal Welfare Code (MAF 2003), sows will only be allowed to by confined in dry stalls for the first four weeks after mating. A transition period is implied, but in 2015, all farms need to have adopted this system.

Growers are raised in intensive grower facilities (conventional pens) or in hoop structures with deep litter systems. Whilst the flooring in conventional pens is generally made of concrete or plastic slats, bedded hoop structures have a floor base of straw or sawdust (deep litter). Furthermore, hoop structures often accommodate larger groups of pigs (100 to 200 pigs) than conventional pens (10 to 30 pigs). Hoop structures have been promoted as low-cost, welfare-friendly systems with good health and performance standards. However, the profitability of hoop structures was recently affected by increased straw prices. Housing pigs in conventional pens bears the advantage that pigs are easier to manage and control and that they are less affected by environmental influences (e.g. environmental temperature).

2.2 Definition of production measures

2.2.1 All-in/All-out management

With increasing specialization, All-in/All-out (AIAO) management has largely replaced continuous flow management of grower pigs. AIAO can be described as a management system, where groups of pigs (‘batches’) of approximately the same age enter and leave a location at the same time. Between batches, the location is thoroughly cleaned, disinfected and left empty for several days. This leads to improvements in the overall hygiene level and air quality, which further reduces the spread and severity of diseases. It has been repeatedly shown that pigs reared in AIAO systems have better growth performance (Scheidt, A., Clark, K., Mayrose, V., Cline, T., Jones, D., Frants, S. 1990; Ice et al. 1999) than pigs reared in continuous flow systems. Furthermore, mortality rates (Losinger et al. 1998b) and levels of respiratory disease (Scheidt, A., Clark, K., Mayrose, V., Cline, T., Jones, D., Frants, S. 1990; Ice et al. 1999) were reported to be lower in AIAO than in continuous flow systems.

Split marketing is often combined with AIAO management. Weight variation among market animals within a batch as well as premiums paid by processors for uniformity constrain producers from marketing the entire batch at one time. Hence, many pig producers employ split marketing of the heaviest pigs from individual batches.

Commonly, the heaviest 25 to 50% of the animals from a batch are marketed one to two weeks earlier than the remaining animals. This practice can reduce production costs by lowering total feed costs and can improve income because a greater number of animals can be marketed at desirable weights.

2.2.2 Measures of grower herd performance

2.2.2.1 Direct measurements

Numbers of pigs at barn entry, transfer and market as well as number of deaths are simple, but important records in the grower unit. Based on these numbers, the pig inventory of an active batch of pigs can be continuously adjusted every day. The daily-adjusted pig inventory is then added to the cumulative number of pig days of a batch, which is used to calculate average mean parameters per pig in a batch (e.g. mean age at market, mean daily feed intake).

Ages are calculated from the entry age to the grower herd, the date of entry and the date of the event of interest. Time to market may either be expressed as ‘Age at market’ or as ‘Days to market’. ‘Days to market’ is the preferable measure if the entry age is not exactly known.

Weights can be obtained throughout production as live weight and at slaughter as carcass weight. Either individual pigs or groups of pigs (e.g. pen, batch) can be subject of weight measurements.

Sample weights refer to weights obtained in pigs before market weight, so that early inferences can be made on batch performance.

Variation in weaning numbers, body weights, growth rates, feed intake and back fat has an important impact on productivity and profitability. Variation is often expressed in units of standard deviation. However, if variation is to be compared at different mean values, then coefficient of variation (CV) is the preferable measure, which relates the standard deviation to the mean.

Variation in body weight within a batch is highly variable between farms. Economic penalties of high variation occur when pigs of wide weight ranges are to be marketed and when lightweight pigs need to be sold below optimum weight. Reports about general values of variation are rare. Payne (1999) suggested a CV in body weight of 15 to 18% for batches at 20 to 25 kg live weight and a CV of 10% at market weight based on experience from research and commercial facilities. These values are lower than values reported by Buddle (1997), who divided 32 Australian pig farms in three health categories. The coefficient of variation in weaning weight was 25.2%, 19.6% and 17.7% for the lowest, medium and highest health category, respectively. Variation in weaning weight is highly dependent on variation in weaning age. In a study of Dewey (2000), CVs in weaning age on eight Ontario farms ranged from 17 to 37%. In addition, variation in growth potential, feed intake, management and disease are known factors to influence body weight variation between individual pigs (Payne et al. 1999).

Feed intake should be termed correctly as feed disappearance when feed wastage is not measured. Feed consumption is the appropriate term if feed wastage has been measured and subtracted from the feed disappearance. Feed wastage is routinely neither measured on farms nor in studies investigating the effect on feed intake. Hence, feed intake generally refers to feed disappearance. This means that variations in study findings regarding feed intake may be partly due to differences of feed wastage.

Feed wastage can be highly variable between farms (Schinckel et al. 1996; Porkma$ter 1997). For instance, measurements ranged from 1% to 25% in the study of Baxter (1991). Various factors influence feed wastage including feeder type, feeding method and feeder space. For instance, trough feeding increased feed wastage, whereas feeders with head barriers reduced feed wastage in the study of Baxter (1991).

Back fat is routinely measured at slaughter as a determinant of the carcass value. In live animals, back fat depth can be assessed using ultrasound measurements. Back fat ultrasound measurements were shown to be highly correlated with back fat measurements at slaughter (Chiba 1995). The site of measurements is generally at the 10^{th} rib, two to three cm lateral of the midline.

2.2.2.2 Indirect measurements

Growth rate is the weight gain over a defined period divided by the number of days within this period. This parameter can be used to express the growth rate during a specific production stage, during the growing period only or during the entire life (from birth to market). If the start point for growth rate calculation is the date of birth, birth weight should be subtracted from the final live weight to obtain weight gain. A common estimate for birth weight is 1.5 kg if real data are not available (Schinckel et al. 1996).

Feed conversion ratio is the ratio of the amount of feed delivered to the live weight gain during this period. Carcass feed conversion ratio estimates the amount of feed used for each kg of carcass weight gain. Feed efficiency or gain to feed ratio is the reciprocal term of feed conversion ratio, thus dividing live weight gain by feed consumption. A beneficial development changes feed conversion ratio in a negative (decrease) and feed efficiency in a positive manner (increase). Hence, feed efficiency is used as the preferred term here, as it is more intuitive.

A National Survey in the USA (Losinger 1998a) reported values of live weight feed conversion ratio during the grower/finisher phase ranging from 2.18 to 5.91 kg/kg gain with a mean of 3.28 kg/kg (SD ± 0.52 kg/kg). Across the 212 pig units, 40.6% of the farms characterized the values for feed conversion ratio as guessed and 59.4% indicated that the values were based on actual measurements. This highlights that there is a wide range in feed efficiency of grower/finisher units, which indicates opportunities for improvement. Furthermore, it shows that despite the high impact of feed efficiency on farm profitability, it appears that this parameter is not routinely monitored in modern pig production.

Mortality and morbidity rate is the proportion of deaths and sick/injured animals, respectively, to the total number of pigs entered (overall growing period or specific production stage). Mortality rate may vary widely on commercial farms because of differences in management practices, housing conditions and disease status. Generally, patterns are seen in the age distribution of deaths in commercial farms. The highest mortality rates generally occur in the first four weeks post-weaning and in the late finisher phase. From 28 Australian farms, post-weaning mortality rate was 4.6% (SD 3.3%) in farms with low health status (n = 6), 1.1% (SD 1.6%) in farms with medium health status (n = 15) and 0.2% (SD 0.8%) in farms with high health status (n = 7) (Skirrow et al. 1997). This is similar to a post-weaning mortality rate of 1.9% reported for 106 French farms (Madec et al. 1998). A national survey of 393 US grow-finish farms indicated that 63.6% of the producer had mortality rates of less than 2% during the grow-finish, which included pigs of approximately 60 to 180 days of age (Losinger et al. 1998b). Mortality rates were higher in late finisher pigs than in early finisher pigs in the study of Maes (2001b) and Morrison (2001). Economically, late mortality imposes a greater opportunity cost to the producer than early mortality.

Furthermore, a seasonal pattern in mortality rate exists. For instance, Morrison (2001) who described patterns in mortality over a four year period observed a peak in finisher mortality in late autumn and early winter, while a less pronounced peak in weaner/grower mortality occurred during autumn.

Pathological and clinical examination of affected pigs makes mortality and morbidity data more valuable for diagnosis and interpretation. In the study of Morrison (2001), necropsy data on approximately 600 pigs (summer 1999) revealed that pneumonia was the most frequent cause of mortality followed by gastric ulcers. Similarly, Straw (1983) analysed mortality in more than 1500 barrows from approximately 20 kg up to market weight. The study identified respiratory disease as the most frequent reason of death (24.7%), followed by gastric ulcers (14.0%) and enteritis (6.4%).

Killing-out percentage is the proportion of carcass weight to live weight in percent. The body components that do not contribute to carcass weight are intestinal contents, organ weight, blood and offal (Figure 2.2.1). It may vary between countries whether the pig head is included in carcass weight. For instance, carcass weight includes the head in New Zealand (head-on), whereas it does not include the head in Australia (head-off).

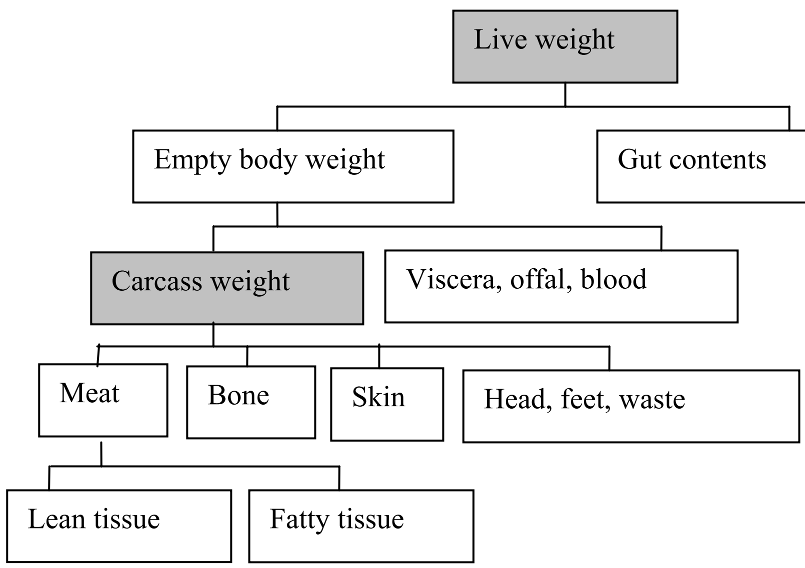

Figure 2.2.1. Slaughter components of the pig. Killing-out percentage is calculated by dividing carcass weight by live weight (shaded boxes).

Killing-out percentage needs to be estimated if the producer wants to determine the live weight at market selection, which converts to the desired carcass weight. Furthermore, if carcass weight is the only final weight measurement, it needs to be converted to live weight to calculate live weight growth rate and feed efficiency as performance parameters.

Apart from dressing procedures (e.g. head-on vs. head-off), gut fill and organ weight have the greatest impact on killing-out percentage. Variables influencing gut fill and organ weight are in particular the size of the pig, time of last feed, feed intake and the rate of metabolism, the latter two of which further depend on season, disease and feeding intensity. Despite the variety of those factors, literature has paid little attention to quantify the response in killing-out percentage to those factors in terms of mathematical equations or adjustment factors.

2.2.2.3 Measures of breeding herd performance

Parity number of multiparous sows influences litter size (Le Cozler et al. 1997; Hughes 1998), pre-weaning mortality rate (Daza et al. 1999a), milking ability (Daza et al. 1999b) as well as maternal antibody transfer (Klobasa et al. 2004), all of which may have consequent effects on pre- and post-weaning growth. Furthermore, gilts differ from multiparous sows in that they generally have smaller litters (Koketsu 2005), produce less milk (Daza et al. 1999b), and have lower colostral antibody titres (Calsamiglia et al. 2000) than multiparous sows.

Litter size may have an effect on post-weaning growth rate since pigs in larger litters show generally a greater variation in birth weight (Milligan et al. 2002), which further affects survival rate and variation in subsequent weights. Furthermore, there is evidence that litter size has an adverse effect on pre-weaning piglet growth rate (Auldist et al. 1998). Even though total daily milk production (kg/day) increases linearly with each additional piglet per litter (Auldist et al. 1998; Daza et al. 1999b), milk production per weaned piglet decreases with every additional piglet per litter (Daza et al. 1999b).

Pre-weaning mortality rate (excluding stillborns) may serve as an indicator for disease events or adverse environmental conditions throughout the nursery phase, which may have subsequent negative effect on post-weaning growth. Furthermore, variation in weaning age between litters (‘Coefficient of variation in weaning age’) may have an effect on subsequent growth performance, since it affects weight variation at subsequent growth stages.

2.2.3 Measures of cost and profit

Total cost in pig production is composed of fixed and variable costs. In general, fixed costs do not depend on the quantity of production. However, fixed costs expressed per unit of product decrease when production increases, because it is being distributed to a higher quantity. In contrast, variable costs depend on the production quantity. If amount of production increases, variable costs tend to increase as a total, but remain similar when being expressed per unit of product.

Feed cost is the greatest variable cost. Estimates for the proportion of grower feed contributing to the total feed cost on a typical farrow-to-finish farm range from 60% (Henman 2003) to 75% (De Lange 1999). Therefore, it is useful to distinguish between feed costs and non-feed costs (Figure 2.1.1) instead of distinguishing between fixed costs and variable costs.

Non-feed costs include labour, veterinary service, building cost, electricity, interest rate and others. When expressed per kg carcass weight produced, non-feed costs are primarily determined by the quantity of weight produced and the rate of weight gain. Therefore, throughput must be maximised to reduce non-feed costs. **Feed cost per kg carcass weight** is driven by feed efficiency and feed cost per ton of feed. Feed cost per ton of feed is further determined by the price of the individual feed ingredients (uncontrollable) and diet composition (controllable). Hence, diet formulation is a vital component of feed cost per kg carcass weight as it affects both, the feed cost per ton of feed and feed efficiency. Feed efficiency furthermore depends on animal, environmental and health factors as well as the amount of feed wastage.

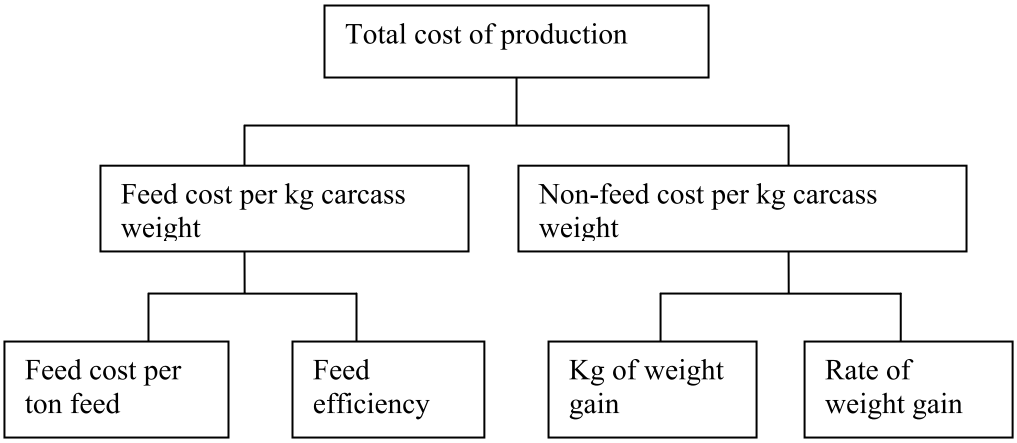

Figure 2.2.2. Components of total cost of production (adapted from Fuchs (2002)).

Profitability in the grower herd depends on revenue, fixed and variable costs, whereas gross margin depends on revenue and variable cost. A common measure of profit used on farms is 'Margin over feed cost per pig sold' (Dritz et al. 2002), which is calculated as the margin between the average price received per pig and the average feed cost per pig. However, the 'Margin over production cost expressed per pig place per year' is a more meaningful measure since it incorporates throughput as well, thus reflecting the true profit of the pig unit given its production capacity (Whittemore 1993; Brumm 1995).

Xue (1998) investigated factors influencing feed cost per kg weight gain on five U.S. pig farms over a two year period. The study found that farm ($P < 0.007$), month ($P < 0.0001$), feed efficiency ($P < 0.0001$), feed cost per kg feed ($P < 0.0001$), and initial weight ($P < 0.05$) significantly influenced feed cost per kg weight gain. These parameters explained 99.5% of the variance in feed cost per kg weight gain. Similarly, an epidemiological study by Vantil (1991) investigated factors explaining variations in return to management and labour (RML) on eleven Canadian farrow-to-finish operations. Return to management and labour was defined as the total revenue minus all expenses except labour, thus being an indicator of fixed costs. The study found that RML was best predicted ($R^2 = 0.648$) by pigs marketed per square meter per year ($p = 0.008$) and pigs marketed per sow per year ($p = 0.096$), whereas biological parameters had limited ability to predict fixed costs ($R^2 = 0.307$). In contrast, 94.3% of the variation in variable costs could be explained by feed cost per kg gain ($p < 0.0001$) and pigs marketed per sow per year ($p = 0.044$). These findings support the associations between production and economic parameters as outlined in Figure 2.2.2.

2.3 Epidemiology

The field of veterinary epidemiology is traditionally concerned with disease control/prevention as well as with optimization of livestock production (

Figure 2.3.1). However, the focus of epidemiology does not lie on curing the disease or the production problem. In contrast, it aims to use knowledge about the complex interactions causing the disease or production problem to prevent them in the first place. Hence, 'Preventive Veterinary Medicine' is another term used for 'Veterinary epidemiology'.

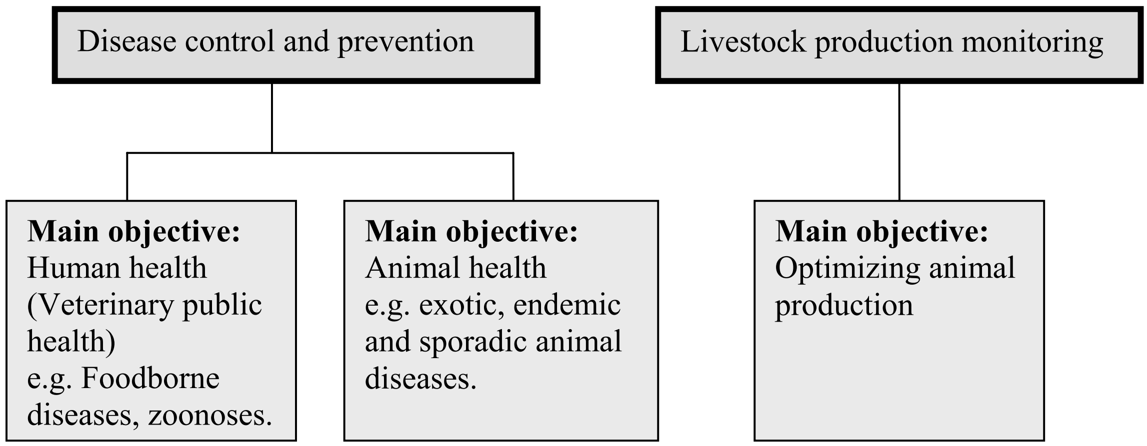

Figure 2.3.1. Areas of veterinary epidemiology.

Epidemiology includes both, field control programs and research (Dohoo 1993). Especially over the last decade, the benefits of epidemiological field control programs have been increasingly recognized. Several studies showed the benefits of applying epidemiological knowledge in the field (Horst et al. 1996; Horst et al. 1998; Van Schaik et al. 1998). Nowadays, a wide range of parties such as governments, large scale organizations (e.g. OIE, WHO, FAO), veterinarians and farmers' associations base their decisions on epidemiological investigations.

Simultaneously, epidemiological research has vastly expanded over recent years. The aim of epidemiological research is generally to identify potentially causal associations between investigated factors and outcomes. Factors may be individual attributes or exposures. Whilst individual attributes are intrinsic characteristics of the individual (e.g. age, sex, breed, weight), exposures are external characteristics in the environment (e.g. nutrition, housing) (Dohoo et al. 2003). Factors are termed risk factors if they show a significant statistical association with the outcome. After determination of risk factors, general inferences are made about ‘causation’ considering the effect of potential confounders, which present one source of bias. Bias, in general, may be defined as a systematic (as opposed to random) departure from true values. Examples for other sources of bias are measurement bias and sampling bias.

Observational studies are the predominant study type used in epidemiological studies in contrast to experimental studies. Experimental studies avoid confounding factors by collecting data in a controlled environment. In contrast, observational studies aim to investigate animals in their natural state. This allows to understand the complex web of relationships and interactions that affects animals in their natural state (Schwabe 1993; Dohoo et al. 2003). Observational studies in general have the advantage that they are supposedly non-invasive and relatively low cost. Consequently, they are easier to conduct over prolonged periods than experimental studies. However, observational studies are more susceptible to bias than experimental studies. This potential of uncontrolled confounding requires careful interpretation of results from observational studies.

Although observational studies have been traditionally used in epidemiology, complexities such as clustering have not necessarily been correctly addressed. This was clearly shown by McDermott (1994) who investigated 67 papers dealing with clustered data, which were published in the first ten volumes of the journal *Preventive Veterinary Medicine*. Twenty of 67 included papers did not correctly account for clustering resulting in incorrect inferences drawn from the data. Especially since the early 1970’s, a lot of progress has been made in analytical epidemiology. Much of this progress was facilitated by the development of highly sophisticated computer technology and software development. Consequently, statistical methods available at present allow dealing with many analytical complexities encountered in epidemiological studies.

2.4 Analytical methods

2.4.1.1 Autocorrelation in longitudinal data

The analysis of measurements over time (longitudinal or time series data) is a common task in epidemiology. When performing multivariable analysis on time series data, the error (or residual) series is often not independent through time. Instead, the errors are serially correlated or autocorrelated. Another problem arises when the error variance is not constant, that is the errors are heteroscedastic. Residuals are positively autocorrelated when adjacent residuals are clustered by sign and are negatively autocorrelated when a residual tends to be followed by a residual of the opposite sign. However, high autocorrelation in model residuals may also indicate a lack of model fit.

Stationarity is a basic assumption of time series techniques. A time series is stationary if both the mean and the variance of the series are independent of time. A time series is autocorrelated if it is non-stationary in its mean, whereas it is heteroscedastic if it is non-stationary in its variance. Typical examples for non-stationary patterns include the presence of a deterministic trend or seasonality. Autocorrelation estimates may be biased if a time series is non-stationary. For instance, results from the study of Yue (2003) indicate that the presence of a deterministic trend overestimates positive serial correlation und underestimates negative serial correlation.

There are different methods to achieve stationarity in the mean (differencing, detrending, decomposition) and in the variance (variance stabilization transformations) (Wei 1990). However, when doing multivariable analysis, we do not know how much of the non-stationary time patterns are explained by the predictor variables, which present time series themselves. Hence, alternative techniques need to be considered when performing a multivariable analysis.

2.4.1.2 Multivariable analysis of autocorrelated data

Ordinary least squares analysis is the most common method used to perform multivariable regression analysis. Ordinary least squares (OLS) estimators have minimal variance when the residuals are uncorrelated (e.g. no autocorrelation) and have constant variance (homoscedasticity). Due to their simplicity, OLS estimators are frequently computed when the residuals in truth are autocorrelated. However, the existence of serial correlation alters the variance of the OLS estimators, leading to biased significance values.

Positive autocorrelation leads to an underestimation of the error variance and thus to a rejection of the null hypothesis when in fact it is true (Type I or alpha error) (SAS 2003). In contrast, negative autocorrelation results in an overestimation of the error variance and thus to a failure to reject the null hypothesis when in fact it is wrong (Type II or beta error).

Depending on the pattern of serial dependency, autocorrelated data can be modelled in different ways. The simplest form of modelling autocorrelation is autoregression. An autoregressive process, AR(p), is a linear function of past values plus a random shock:

$$y_t = \nu + \sum_{i=1}^{p} \phi_i y_{t-i} + \varepsilon_t ,$$

where ν is a constant, ϕ_i are unknown autoregressive parameters, y_{t-i} is the observation at time lag i and ε_t is the error term (Nemec 1996). It is important to note that negative coefficients of AR parameters should be interpreted as a positive autocorrelation, whilst positive coefficients indicate negative autocorrelation.

Another simple model for autocorrelated data is the moving average. A moving average model is an unevenly weighted process of random shock series ε_t:

$$y_t = \nu + \varepsilon_t - \sum_{i=1}^{q} \theta_i \varepsilon_{t-i}$$

where ν is a constant, θ_i are unknown moving average parameters, ε_{t-i} is the error term at time lag i and ε_t is the error term at time t (Nemec 1996).

In summary, the autoregressive model (AR) includes lagged terms of the time series itself and the moving average model (MA) includes lagged terms of the error. Random shocks of the AR(p) model persist indefinitely, although its magnitude diminishes over time. In contrast, random shocks of the MA(q) model is a weighted sum of the past random shocks and persists no longer than for q periods (Choudhury et al. 1999). When both components are present in a time series, then the series follows an autoregressive-moving average, or ARMA(p,q), model, where p indicates the order of the autoregressive model and q the order of the moving average model.

Autocorrelation patterns of stationary time series can be identified at different time lags (time intervals) by means of diagnostic plots, such as the autocorrelation function

(ACF) and the partial autocorrelation function (PACF) (Wei 1990). Both functions measure the linear predictability of the series at time t. However, prior to that, the PACF removes autocorrelations after fitting autoregressions of order k (Nemec 1996). The combined use of these two diagnostic plots gives an indication of the order and the type of the underlying time series process. If the time series follows an autoregressive process of order p (AR(p)), then the ACF decays exponentially or shows damped sine waves, whereas the PACF dies out after lag k. On the other hand, if the series follows a moving average process of order q (MA(q)), the ACF dies out after lag k, whilst the PACF decays exponentially or shows damped sine waves. In case of an ARMA(p,q) model, both the ACF and PACF decay exponentially or show damped sine waves.

Regression analysis with autoregressive error correction ('autoregressive model') is a method to perform multivariable analysis of correlated data. This method is based on ordinary least squares regression whilst assuming that an autoregressive process generates the residuals. By simultaneously estimating the regression coefficients β and the autoregressive error parameters, the model corrects the regression estimates for autocorrelation. Several studies have applied this technique in pig research (Baadsgaard et al. 2004) as well as in other disciplines (Rosel et al. 2000; Haidich et al. 2001; Smith, R. F. et al. 2003; Miller et al. 2004). An autoregressive model includes two components, (1) predictor variables (= structural part of the model) and (2) autoregressive parameters taking into account the information from past residuals. Hence, an autoregressive model produces two different R-squared values depending on what components are included. The 'Regression R^2' results from the structural part of the model alone, whereas the 'Total R^2' is based on the overall model. The reader is referred to Nemec (1996) for a detailed illustration of autoregressive models and how these are fit in the statistical software package SAS.

The advantage of the autoregressive model is that regression parameter estimates are easier to obtain when the error component is modelled as an AR process rather than a MA or ARMA process (Choudhury et al. 1999). Furthermore, since the method is based on OLS analysis, model-building strategies are identical to traditional model building strategies. However, careful attention needs to be paid whether the series actually follows an autoregressive process. Engle (1974) showed that sometimes it is better to ignore autocorrelation and to use an OLS-model than to incorrectly assume that the series follows an autoregressive process. However, many time series follow a simple autoregressive process. MA or ARMA processes are often found in more complex series, which include strong seasonality or data irregularities. For instance, outliers introduce a particular dynamic in the time series, often resulting in negative MA errors (Haldrup et al. 2005).

2.4.1.3 Missing values

Missing data are a common feature of observational studies and may result in biased estimates and/or loss of power. Several techniques exist to deal with missing values, such as deletion of observations, use of indicator variables and a variety of imputation techniques (Little et al. 1987; Harrell 2001). Generally, the choice of how to deal with missing values depends on the type of missingness, the number of missing data points and the structure of the data set.

It can be distinguished between three types of missingness: (a) missing completely at random, (b) missing at random and (c) informative missing. If data are missing completely at random (MCAR), their missingness is completely unrelated to any characteristics or responses for the subject. If data are missing at random (MAR), the probability that a value is missing depends on values of other variables but not on the value of itself. Clustering of missing values in time is an example of MAR. In contrast, informative missingness (IM) implies that elements are more likely to be missing if their own true values are systematically higher or lower than non-missing values. MCAR is the easiest case of missingness to handle as information from the related measurable variable can be taken into account without creating any bias. If data are IM, no method will adequately reduce bias due to missing values.

Casewise deletion is a traditional approach to deal with missing values, and is generally the default option in most statistical packages. Casewise deletion is achieved by deleting any observations with a missing value. Many researchers consider this as a conservative approach, since no data are ‘made up’. If data are MCAR, then the reduced sample will be a random sample of the original sample resulting in unbiased statistical results (Acock 2005). Therefore, if data are MCAR, the only disadvantage derives from a reduction in sample size and hence a loss in power. However, if data are MAR, casewise deletion may lead to both, a loss of power and biased analytical estimates (Anderson et al. 1985).

Substituting missing values by some reasonable guess, and then analysing the data set as if there were no missing data is called imputation of missing values. The simplest approach is to impute one single estimate for all missing data, such as imputing the mean value of the valid data (‘Mean substitution’). It can be argued that the mean of normally distributed data presents a reasonable guess for a random sample. However, it has been consistently shown that this is the worst method of dealing with missing data (Engels et al. 2003; Olinsky et al. 2003), since imputing one single value for several observations artificially decreases the variance in the data leading to considerable bias.

When each missing data point is imputed using a different value, this can either be achieved by substituting one value for each missing value (‘Simple imputation’) or by using a combined value from multiple imputations (‘Multiple imputation’), hence accounting for uncertainty in the missing value estimate. Regardless of whether simple or multiple imputations are used, different cross-sectional methods can be applied to obtain the estimates such as regression methods (based on valid predictor and/or outcome variables) or expectation maximization. The reader is referred to recently published papers for comparison and discussion of these methods (Twisk et al. 2002; Olinsky et al. 2003; Barzi et al. 2004; Acock 2005; Moons et al. 2006; Van der Heijden et al. 2006).

Generally it can be said that if less than 5% of the data set includes missing values, then the choice of imputation method is not very relevant (Harrell 2001). In addition, casewise deletion of missing values requires that (1) data are MCAR and (2) datasets are large. If less than 10% of the data include missing values, simple imputation performs similarly to multiple imputation (Barzi et al. 2004). Multiple imputation of missing values appears most appropriate if more than 10% of the data include missing values (Barzi et al. 2004). However, in a study, where 38% of the observations included missing values, no difference was found between single and multiple imputation methods (Van der Heijden et al. 2006). None of the described methods will provide valid estimates, if more than 60% of the data are missing (Barzi et al. 2004).

Data discontinuities raise a particular problem if time series methods are to be applied, which generally require continuous data points (Harvey et al. 1998; Junninen et al. 2004). If the data set includes *intermittent missing values* (missing value followed by an observed value), imputation techniques allow maintaining a continuous time series. In contrast, if missing values appear after the beginning or before the end of the time series (*embedded missing values*), casewise deletion may be considered a feasible option to reduce bias due to missing values.

It was shown for longitudinal data that imputation methods accounting for the longitudinal structure of the data set were more efficient than cross-sectional imputation methods (Twisk et al. 2002; Engels et al. 2003; Barzi et al. 2004; Junninen et al. 2004). The simplest longitudinal imputation method is the nearest neighbour imputation, in that the nearest end-point of the gap is used as the estimate. Other methods, such as longitudinal interpolation or longitudinal regression as described by Twisk (2002) or stochastic estimation maximization (Gad et al. 2006) are alternative options. Similar to the comparison of single and multiple imputations, if less than 10% of a variable are missing, a simpler method such as nearest neighbour imputation appears to be sufficient to provide reasonable imputation estimates (Twisk et al. 2002; Junninen et al. 2004).

Chapter 3 Materials and Methods

3.1 Study design

A longitudinal study with both prospective and retrospective data collection was conducted on three commercial farrow-to-finish pig farms in New Zealand. The farms were enrolled in the study between April and July 2003 as a convenience sample based on the following criteria:

- Established data recording system for the grower herd;
- Perceived willingness of the farmer to participate in the study as determined by their veterinary consultant.

At the commencement of the study, routine data collection procedures of farms were adopted without changes. Throughout the study, farm staff continuously performed data collection and data recording. Data entry was carried out by farm staff (farm A) or by the investigator (farms B and C). Data collection and data entry for the purpose of the study were discontinued in August 2004 (farm A), September 2004 (farm B) and June 2005 (farm C).

At the time of enrolment, the researcher visited each farm for a minimum period of one week to become acquainted with farm management and data recording practices. At the same time, data entry into a specialized grower herd recording system (PigGAIN[1]) was initiated (farms B and C) or verified (farm A). The aim of data collection was to record pig numbers, ages and weights as well as feed deliveries. Retrospective data (batch open date prior to study start) were accessible for more than twelve months on farms A and B. These data were included if, as a minimum requirement, batch-specific entry and move out records (numbers and weights) were available.

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1 PigGAIN is a software component of PigWIN, developed by the New Zealand Pork Industry Board and registered to FarmPro Systems Ltd, Palmerston North, New Zealand.

3.2 Description of the farms

The three farms were indoor units in the North Island. Farms A, B and C were located in the Taranaki, Manawatu and Hawkes Bay region, respectively (Figure 3.2.1).

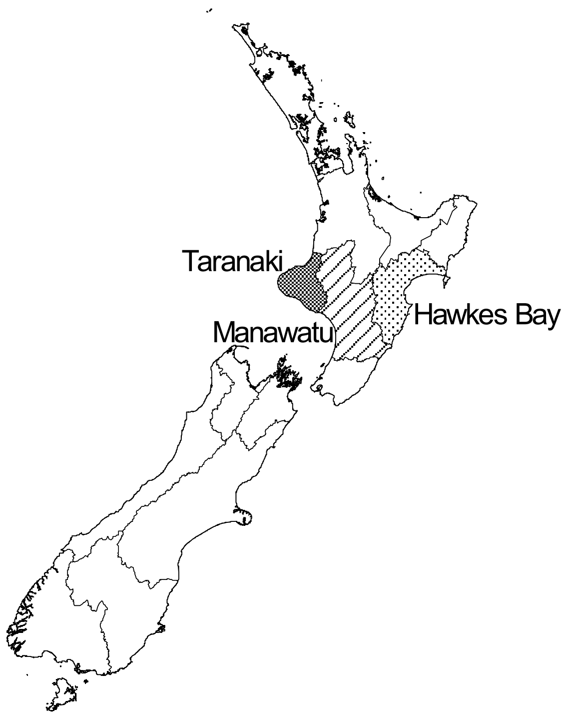

Figure 3.2.1. Location of studied pig farms within regions in New Zealand. Farms A, B and C were situated in the Taranaki, Manawatu and Hawkes Bay region, respectively.

3.2.1 Breeding herd

All farms derived their progeny from crossbred Large White x Landrace breeding stock. The average breeding herd size was 400, 280 and 230 sows on farms A, B and C, respectively. During the suckling period, all farms housed piglets with their dam in farrowing crates. Handling of piglets involved teething and tailing as well as one iron injection within the first couple of days. Furthermore, piglets were vaccinated twice against Mycoplasma hyopneumoniae. It was routine practice on farm C to tube-feed weak piglets with cow colostrum within the first 24 hours of life. Piglets were offered creep feed towards the end of the suckling period on all farms.

3.2.2 Pig flow

All studied farms weaned pigs in weekly intervals. Subsequently, pigs were managed using an All-In/All-Out (AIAO) system, which implies that pigs were moved in and out of buildings as separate groups (batch production). However, at marketing, batches were sold in several lots (split marketing) to increase the number of pigs being sold at optimum marketing weight. Figures 3.2.2 to 3.2.4 describe the conceptual pig flow during the growing period on each farm. Housing conditions in the special rearing location (SRL) differed from the housing conditions in the weaner shed in that piglets in the SRL were housed at higher temperatures and were fed diets of greater nutrient density.

Farm A weaned piglets at approximately five weeks of age. Farm staff moved the lightest weaned pigs to a SRL, which operated on a continuous flow system. Pigs originating from both, the farrowing room and from the special rearing location were moved to the weaner shed to form a new batch. Typically, batches were transferred to the grower and finisher sheds at 23 and 48 days post-weaning, respectively. Sick or injured pigs were moved to hospital pens that housed pigs from different age groups.

Weaning management was changed shortly prior to the end of the study. The new weaning procedure implied that piglets were weaned at four weeks of age, but remained in their accustomed farrowing room for one week before being moved to the weaner room.

Farm B weaned piglets at four weeks of age. The lightest weaned pigs entered a special rearing location (SRL), whilst the remainder of the weaned pigs formed a new batch together with the heaviest piglets from the SRL. Although the age groups in the SRL were housed separately, the specific age of pigs originating from the SRL was not consistently recorded. Pigs were transferred to the grower and finisher sheds at 43 and 78 days post-weaning, respectively. Sick or injured pigs were moved to hospital pens, which held pigs from different age groups.

Farm C weaned piglets into the weaner location at three to four weeks of age. Pigs were transferred to the grower and finisher sheds at 48 and 75 days post-weaning, respectively. This farm neither operated a special rearing location nor specific hospital pens.

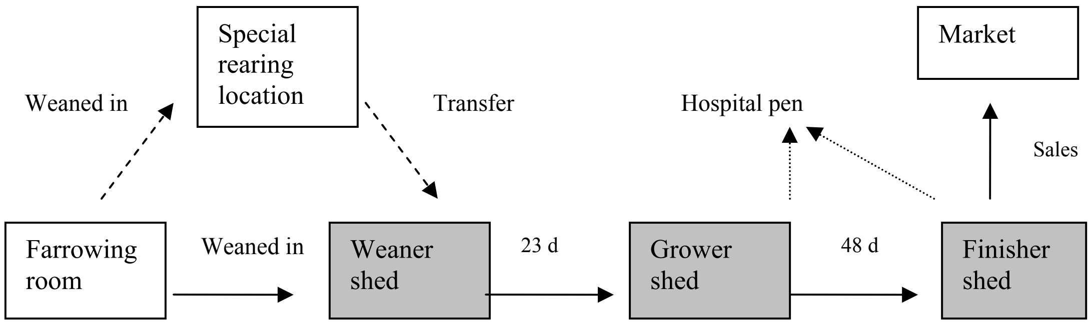

Figure 3.2.2. Characteristics of pig flow on farm A. Time periods between grower herd production stages are displayed in days (d) after entry to the weaner shed. Shaded boxes indicate monitored production stages.

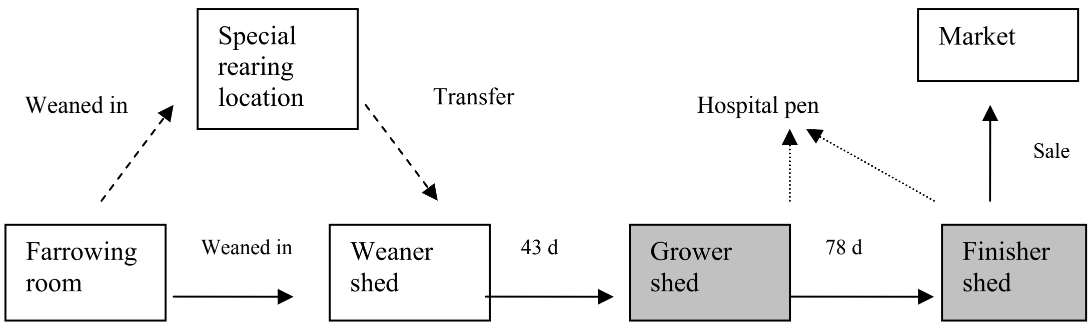

Figure 3.2.3. Characteristics of pig flow on farm B. Time periods between grower herd production stages are displayed in days (d) after entry to the weaner shed. Shaded boxes indicate monitored production stages (no data collected at the weaner stage).

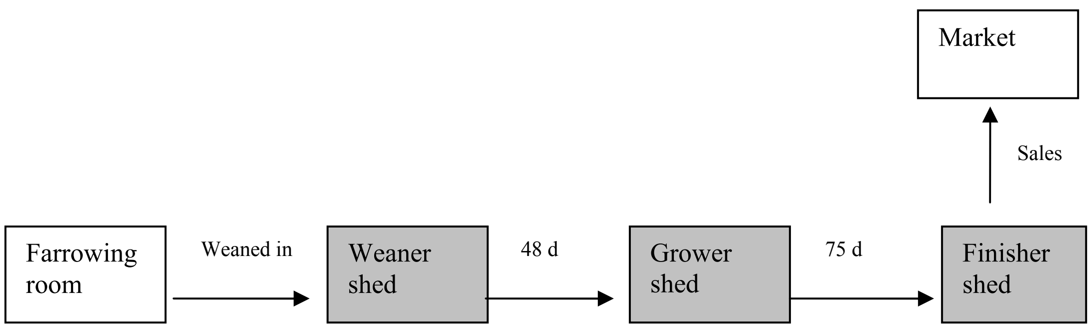

Figure 3.2.4. Characteristics of pig flow on farm C. Time periods between grower herd production stages are displayed in days (d) after entry to the weaner shed. Shaded boxes indicate monitored production stages.

3.2.3 Housing facilities

Characteristics of housing facilities are summarized in Table 3.2.1. Differences in housing facilities are described as follows.

On farm A, the weekly pig holding capacity of housing facilities was 160 pigs. This farm housed boars and gilts in separate pens (split-sex housing) throughout production. The farm operated two finisher sheds of equal design. Each finisher shed housed one batch in the middle section and four batches in the outer section. Pens in the middle section were of greater dimension (eight pens per batch with 20 pigs per pen) than pens in the outer section of the shed (ten pens per batch with 15 pigs per pen).

On farm B, the housing facilities allowed raising 120 pigs per week. This farm housed pigs in pens as mixed-gender groups. Four sheds (sheds A, B, C and D) were used at the finisher stage. Sheds A and B had the same shed characteristics and were hence considered the same shed type (type A). Both sheds housed two batches each in partly slatted pens with 10 pigs per pen. Shed C (shed type B) also housed two batches at a time in partly slatted pens. However, pens were of greater dimensions (20 pigs per pen) than pens in shed type A. Shed D (shed type C) consisted of lined up concrete pens open to one side above pen partitioning. This shed housed one batch with 20 pigs per pen. Six extra pens in a separate shed (shed E) were used to house surplus pigs at the grower and finisher stage. These pigs received feed ad-libitum from a wet-dry feeder, in contrast to the remainder of the batch receiving feed at the finisher stage via a computerized-liquid feeding system.

Farm C had a weekly pig holding capacity of 80 to 100 pigs per batch. At weaning, pigs were moved into deep litter straw-based sheds as a single mixed-gender group. At transfer to the grower shed, a batch was split into sub-groups of ten pigs, which were housed in mixed-gender pens. Later on, each pen of pigs was moved to lined-up finisher pens, which were open to one side above pen partitioning.

Table 3.2.1. Main characteristics of grower herd facilities on the three studied New Zealand pig farms.

Stage	Features	Farm A	Farm B	Farm C
Weaner				
	Number of sheds	1	1	1
	Number of batches per shed	4	6	7
	Number of pens per batch	8	6	1
	Number of pigs per pen	20	20	NA [b]
	Flooring	Partly slatted	Partly slatted	Deep litter
	Ventilation	Forced	Forced	Natural
	Heat source	Heat lamps	Heat lamps	Straw
	Separation of airspace between batches in shed	Yes	Yes	Yes
	Feeding system [a]	Dry	Wet/Dry [a]	Dry
	Access to feed	Ad-libitum	Ad-libitum	Ad-libitum
Grower				
	Number of sheds	1	1	1
	Number of batches per shed	4	6	6
	Number of pens per batch	8	8	10
	Number of pigs per pen	20	13	10
	Flooring	Fully slatted	Fully slatted	Partly slatted
	Ventilation	Forced	Forced and natural	Forced
	Heat source	None	None	None
	Separation of airspace between batches in shed	Yes	Yes	No
	Feeding system [a]	Wet and dry [a]	Wet/dry [a]	Dry
	Access to feed	Ad-libitum	Ad-libitum	Ad-libitum
Finisher				
	Number of sheds	2	4	Rows of pens
	Number of batches per shed	5	1 to 2	NA [b]
	Number of pens per batch	8 to 10	8 to 10	8 to 10
	Number of pigs per pen	16 to 20	10 to 20	10
	Flooring	Fully slatted	Concrete and partly slatted	Partly slatted
	Ventilation	Forced and natural	Forced and natural	Natural
	Heat source	None	None	None
	Separation of airspace between batches in shed	No	No	NA [b]
	Feeding system [a]	Liquid	Liquid	Wet/dry [a]
	Access to feed	Restricted	Restricted	Ad-libitum

[a] Wet/dry feeding: Feeders combined with drinkers so that pigs can mix feed with water; wet and dry: separate liquid and dry feeding.
[b] NA: Not applicable.

3.2.4 Feeding

Farms B and C fed four diets throughout the growing period (creep, weaner, grower and finisher diet). Farm A fed a second finisher diet (finisher diet 1 and 2) in addition to the four diets outlined above. On farm A, bread by-products were fed to grower and finisher pigs, which were substituted with nutrients to meet dietary requirements. Weaner pigs on this farm received grain-based compound creep and weaner diets. In contrast, farms B and C used home-mixed grain-based diets at all production stages. These two farms used barley as the predominant grain source in grower and finisher diets, whereas they used wheat as a common component of weaner diets and sometimes of grower diets. Feeding methods (dry, wet/dry, liquid) and feed allowance (ad-libitum or restricted feeding) are described in Table 3.2.1.

3.2.5 Disease status

A veterinarian consultant visited the farms approximately twice a year. Endemic diseases on the farms are described as follows.

(a) Respiratory disease

Mycoplasma hyopneumoniae was endemic on all farms although clinical signs and slaughter findings indicated different degrees of clinical manifestation. *Actinobacillus pleuropneumoniae* was not regarded as a severe problem on any of the three farms.

(b) Enteric disease

Colibacillosis and coccidiosis in weaner pigs and proliferative enteropathy (*Lawsonia intracellularis*) in grower pigs were seen regularly on all farms. Clinical signs of swine dysentery (Brachyspira hyodysenteriae) were not common.

(c) Other diseases

Mange (*Sarcoptes scabiei* suis) had been eradicated on farms A and B. Farm C injected sows with Ivomec (Ivomectin, produced by Merial) prior to farrowing to minimize mite transmission to the offspring.

3.2.6 Specific events occurring on farms

Farm A substantially reduced the use of in-feed antibiotics in 2001. Furthermore, within the last few weeks of the study period, piglets were weaned one week earlier and were left in the farrowing room for six days before they were transferred to the weaner location.

On farm B, it was not recalled that any specific events had occurred over the two and a half year monitoring period.

The pig producer on farm C had only purchased the farm eight months before the start of the study. Progressive replacement of unimproved breeding stock was still ongoing during the first year of the study period. In response to the expected increased proportion of genetically improved grower pigs, dietary changes were implemented in October 2003 for the creep (batches from study week 20 onwards) and grower diet (batches from study week 13 onwards) and in October 2004 for the finisher diet (batches from study week 61 onwards). The change in grower diet affected batches weaned earlier than the change in weaner diet, since seven batches had already entered the grower stage (transfer at 48 days post-weaning). In addition to changes in breeding stock and diets, the pig producer expanded the breeding herd size towards the end of the study period.

3.3 Data collection

Data consisted of production data routinely collected on-farm as well as abattoir data. Financial data were not considered for the study. Batch data were defined as retro- or prospective depending on whether the batch was weaned before or after commencement of the study. Breeding herd production data were routinely collected over the entire study period on farms A and B. However, farm C started recording breeding herd data only after commencement of the study. All farms recorded the date of weaning, transfers and marketing. Differences in data recording practices are outlined as follows.

Farm A counted pigs at weaning, at transfer to the finisher shed and at sale. Feed deliveries of all five diets were recorded at the batch level. Farm staff weighed all pigs at weaning. Furthermore, two pens of pigs were weighed one week after transfer to the grower shed (30 days post-weaning) and two different pens were weighed three times after transfer to the finisher shed in two-weekly intervals (48, 62 and 76 days post-weaning). In the following, these five weight measurements are denoted as sample weight 1 to 5 (WGT 1 to WGT 5). A small portion of pigs was sold privately after they had been weighed on the farm (live weight records). In contrast, pigs marketed at the abattoir were not weighed on-farm prior to market. Carcass weights of those pigs were derived from abattoir data.

Farm B collected data at the grower and finisher stage only. Pigs were counted at transfer to the grower and finisher sheds and at marketing. Farm staff weighed all pens of a batch at transfer to the grower shed and at transfer to the finisher shed (sample weight 1 and 2). Furthermore, all pigs were weighed individually for market selection (market live weight). Feed deliveries and pig deaths were not recorded at the batch level, but only at the shed level, thus not being used for the analysis. Transfer of pigs to hospital pens were recorded on individual pen cards, which were not considered worth processing retrospectively.

Farm C counted pigs at each transfer and at marketing. Farm staff weighed a sub-group of approximately 20 pigs at weaning (sample weight 1) and two pens at transfer to the grower and at transfer to the finisher shed (sample weight 2 and 3). Additionally, all pigs were weighed individually for market selection (market live weight). Feed data were not recorded on the batch level, thus not being included in the analysis.

3.4 Data management and validation

3.4.1 Data management

All data had been initially entered into PigGAIN® (PigWIN® at http://www.pigwin.com). Later on, grower herd records were imported into a customized database (Microsoft Access 2003).

3.4.2 Unit of interest/outcome variable

The unit of interest was the batch, which was characterized in time by its weaning date. All data recorded at the pen or individual pig level were aggregated at the batch level.

The outcome variable was market live weight on farms B and C and carcass weight on farm A. Carcass weights on farm A were derived from abattoir data by assigning the mean carcass weight of the marketing batch to each pig being sold. However, assigned carcass weights were not always truly specific for the grower batch, as a marketing batch may have included pigs from more than one grower batch. Since pigs sold privately on farm A had live weight records only, their carcass weight was calculated based on the PigGAIN® (PigWIN® at http://www.pigwin.com) estimate of killing-out percentage as shown in Equation 3.1, where KO(%) is killing-out percentage and LW is live weight (kg).

$$\mathrm{KO}(\%) = 62.73 - 0.50\mathrm{LW} + 0.013\mathrm{LW}^2 - 6.22 \times 10^{-05} LW^3 \qquad \text{Equation 3.1}$$

3.4.3 Predictor variables

Available predictor variables for each farm and the rationale for their inclusion are presented in Table 3.4.1.

Table 3.4.1. Summary of predictor variables investigated for their association with market weight of grower batches on three New Zealand pig farms and rationale for their inclusion. Availability of parameters is indicated for each farm (Y/-).

Category	Parameter	Farm A	Farm B	Farm C	Rationale for inclusion
Breeding herd parameters					
	Pre-weaning mortality rate	Y	Y	-	Indicator of disease event
	Coefficient of variation in weaning age	Y	Y	-	Disadvantage for small pigs in heterogeneous groups
	Median number of piglets weaned per sow	Y	Y	-	Teat availability, birth weight
	Percentage of gilts farrowed	Y	Y	-	Antibody transfer, milk yield
	Median parity of sows weaned (excl. gilts)	Y	Y	-	Antibody transfer, milk yield
Entry parameters					
	Entry numbers	Y	Y	Y	Stocking rate, indicator for breeding efficiency
	Weaning age	Y	Y	Y	Positive association with weaning weight
	Overall entry age	-	Y	NA [a]	Positive association with entry weight
	Weaning weight	Y	-	-	Positive association with weight at a later stage
	Weight of pigs from special rearing location	Y	-	-	Positive association with weight at a later stage
	Percentage of pigs weaned directly	Y	Y	-	Differences in pig age and developmental state
	Percentage of pigs in separate location	-	Y	-	Differences in housing conditions
Mortality parameters					
	Mortality rate weaner stage	Y	-	Y	Indicator of disease event
	Mortality rate grower stage	Y	-	Y	Indicator of disease event
	Mortality rate finisher stage	Y	-	Y	Indicator of disease event
	Overall mortality rate	Y	-	Y	Indicator of disease event
	Percentage of unaccounted pigs grower stage	-	Y	-	Indicator of deaths and transfers to hospital pens
	Percentage of unaccounted pigs finisher stage	-	Y	-	Indicator of deaths and transfers to hospital pens
	Overall percentage of unaccounted pigs	-	Y	-	Indicator of deaths and transfers to hospital pens
Feed parameters					
	Daily feed intake weaner diet [b]	Y	-	-	Feed intake as a determinant of growth
	Daily feed intake grower diet [b]	Y	-	-	Feed intake as a determinant of growth
	Daily feed intake finisher diet 1 [b]	Y	-	-	Feed intake as a determinant of growth
	Daily feed intake finisher diet 2 [b]	Y	-	-	Feed intake as a determinant of growth

Category	Parameter	Farm A	Farm B	Farm C	Rationale for inclusion
Weight and marketing parameters					
	Sample weight 1	Y	Y	Y	Positive association with weight at a later stage
	Sample weight 2	Y	Y	Y	Positive association with weight at a later stage
	Sample weight 3	Y	-	Y	Positive association with weight at a later stage
	Growth rate from sample weight 1 to 2	-	Y	-	Positive association with weight at a later stage
	Growth rate from sample weight 2 to 3	-	-	Y	Positive association with weight at a later stage
	Growth rate from sample weight 3 to 5 [c]	Y	-	-	Positive association with weight at a later stage
	Days to market	Y	Y	Y	Positive association with market weight
	Age at market	-	-	Y	Positive association with market weight
Other parameters					
	Season	Y	Y	Y	Effect on feed intake and growth
	Pigs housed in middle versus outer pens of finisher sheds	Y	-	-	Different pen design
	Percentage of pigs housed in shed E	-	Y	-	Different housing and feeding conditions
Total number of predictor variables		**25**	**19**	**13**	

[a] NA: Not applicable, since all pigs were weaned directly into the weaner shed.

[b] Recorded feed intake includes actual feed consumption and feed wastage, which could not be distinguished from each other.

[c] Sample weights 3, 4 and 5 on farm A were repeated measurements on the same animal unit, so that growth rate was only calculated between two of these measures. Sample weights 3 and 5 were chosen for the growth rate calculation to cover the longest available time span.

3.4.3.1 Breeding herd data

Litter parameters were recorded at the individual sow level and were stored in PigLITTER® (PigWIN® at http://www.pigwin.com). Measures of litters weaned within the same week (Monday to Sunday) were aggregated at the week-level. These measures included the median parity of sows weaned (excluding gilts), the percentage of gilts farrowed, the pre-weaning mortality rate amongst live born piglets (%), the median weaning age (d), the coefficient of variation in weaning age (%) and the median number of piglets weaned per sow.

3.4.3.2 Counts and ages

The number of pigs entering and leaving a batch was used to adjust the daily pig inventory continuously. The daily pig inventory was further used to calculate the parameter 'Total pig days'. Each day a batch is open every pig of the pig inventory contributes one pig day to the 'Total pig days'. The entry date of a pig was counted as zero, whereas the last study date of a pig (death, move out, transfer) contributed one day to the 'Total pig days'. The parameter 'Total pig days of pigs marketed' was based on the marketed pigs only, counting the cumulative number of days for these pigs from the average start day of the batch to the respective market date of pigs sold. 'Total pig days of pigs marketed' was used to assess specific market parameters such as 'Average days to market' (Equation 3.2).

$$\text{Average days to market (d)} = \frac{\text{Total pig days of pigs marketed (d)}}{\text{Total number of pigs marketed}} \qquad \text{Equation 3.2}$$

The parameter 'Percentage of pigs weaned directly' (farms A and B) was calculated by dividing the number of pigs originating directly from the farrowing room by the total entry number. On farm B, the percentage of pigs per batch raised in shed E during the finisher stage was calculated since these pigs were fed differently from the remainder of the batch ('Percentage of pigs in shed E').

3.4.3.3 Weights

Due to potential deviations from routine weighing days (up to ± 7 days), sample weights were standardized on the typical number of days post-weaning. This was achieved by dividing weights by the actual number of days post-weaning the sample weight was taken and multiplying it by the median number of days post-weaning.

It was suspected that multiple weight measurements on the same pig unit would be highly correlated. Hence, if the same pig unit was used for several sample weight measurements, growth rate between these weight measurements was calculated. An estimated birth weight of 1.5 kg was subtracted from the weight measurement, if growth rate was calculated from birth to a subsequent live weight measurement.

3.4.3.4 Feed

Mean daily feed intake per pig was calculated according to Equation 3.3. On farms B and C, feed deliveries had only been recorded on the silo level, thus not being used for further analysis.

$$\text{Average daily feed intake (kg/d)} = \frac{\text{Total feed delivered (kg)}}{\text{Total pig days in period (d)}} \qquad \text{Equation 3.3}$$

3.4.3.5 Other parameters

All three datasets included a replication of approximately two seasons. Hence, a categorical variable was created for season according to whether pigs were weaned in spring (September to November), summer (December to February), autumn (March to May) or winter (June to August).

On farm A, the effect of middle versus outer pens within shed was considered as an effect in the analysis. Furthermore, the 'Percentage of pigs housed in shed E' was considered as a potential predictor variable on farm B.

3.4.4 Data validation

First, data were investigated for inaccuracies. Unaccounted pigs presented a common source of data error. Unaccounted pigs occurred if recorded entry and move out numbers within a batch did not match at closure date (final pig inventory non-equal zero). The value of unaccounted pigs is positive if the move out number of pigs is lower than the recorded entry number and vice versa. Next, data were inspected for outliers and missing values. Any inconsistencies were compared with the original data sources and/or were verified with farm staff.

3.5 Data analysis

3.5.1 Descriptive analysis

For each farm, a separate model was developed due to differences in recorded parameters and lengths in studied periods.

Normality of continuous variables was assessed using the Kolmogorov-Smirnov test. First, each parameter was plotted over time (time series plot) to explore time patterns visually. Subsequently, the presence of a deterministic trend was investigated. For that purpose, study week was regressed on the variable of interest up to its fifth order polynomial. If several polynomial trend lines turned out to be significant, Analysis of Variance (ANOVA) was used to compare the goodness-of-fit between two significant trend lines. The final choice of the trend line used was based on results from ANOVA and on visual inspection of fitted trend lines. The effect of year, season and their interaction was assessed using Unbalanced One-way Analysis of Variance (Proc GLM).

Growth-patterns of individual batches in relation to days post-weaning (farms A and B) or age (farm C) were explored visually. For that purpose, individual batch-growth curves were plotted and displayed in multiple-plot trellis of graphs for each approximately half-year period.

3.5.2 *Differences between populations*

On farm B, differences in performance between finisher pens housed in sheds A to D and finisher pens housed in shed E were assessed using a two-sample *t*-test (Proc TTEST).

3.5.3 *Missing values*

The missing value prevalence for each predictor variable and the missing value pattern over time were investigated. Missing values in explanatory variables were imputed by the value of the closest valid (generally preceding) measurement to obtain a full dataset ('nearest neighbour imputation'). For study weeks with no weaned batches ('missing observation'), a record was created with all variables set as missing to obtain a dataset with equally spaced observations.

3.5.4 *Analysis of the autocorrelation pattern in the outcome variable*

The autocorrelation structure of the outcome variable was explored by estimating the autocorrelation function (ACF) and the partial autocorrelation function (PACF) (Diggle 1990). ACF and PACF were inspected visually to estimate the order and the type of the underlying time series process. Furthermore, the time series was evaluated for constant variance (homoscedasticity) using the Portmanteau Q-test (Q-test) as well as the Lagrange Multiplier test (LM-test).

3.5.5 *Investigation of collinearity between predictor variables*

First, all bilateral relationships between possible explanatory variables were checked to lower the risk of obtaining results affected by multicollinearity (Dohoo, 1996). Collinearity was regarded as a problem if the correlation coefficient ('r') between two explanatory variables exceeded 0.8. If pairs of highly correlated variables were found, one of them was selected after considering differences in data quality, biological plausibility and strength of association with the outcome variable.

3.5.6 *Multivariable regression analysis with autoregressive error correction*

Identification of risk factors was achieved by using a regression model augmented with an autoregressive model for the random error to account for autocorrelation. Parameters were estimated based on the maximum likelihood method (SAS 2003). The order of the autoregressive term was kept constant throughout model building. Initially, a first-order autoregressive model was evaluated. If residuals of this model type revealed remaining autocorrelation, a second-order autoregressive model was evaluated for its significance. Model selection started with evaluating a univariable model with each independent variable of interest. All significant variables at $P < 0.20$ were offered to the multivariable model ('full model'). A backwards stepwise procedure was used until all predictors had P-values of less than 0.10 ('preliminary main effect model'). Subsequently, predictors not included in the full model were included in the preliminary main effect model one at a time and were kept in the model if reaching P-values of less than 0.10. The significant risk factors in this model were tested for biologically plausible two- and three-way interactions using cross-product terms. Interactions were included in the model one at a time. If several interactions reached P-values less than 0.05, they were included in the model simultaneously and selected following a backwards stepwise procedure. Collinearity of variables was assessed by inspecting any change in signs or standard errors of predictor variables with the inclusion and exclusion of other variables. At last, each variable in the model was excluded one at a time to determine if its inclusion significantly ($P < 0.05$) improved the overall model fit. This was assessed using the -2 Log Likelihood ratio test (Dohoo et al. 2003).

The model was validated by inspection of standardized residuals (raw residuals divided by their standard error) for normality and linearity. Furthermore, model estimates were compared when running the model with and without outliers (outliers: observations that had an absolute value of the standardized residual above 3.3). In addition, residual series were checked for homoscedasticity (Portmanteau Q-test and Lagrange Multiplier test) and residual autocorrelation (Durban Watson test statistic, ACF/PACF).

Furthermore, we checked whether the choice of an autoregressive model was appropriate: For that purpose, we fit selected predictor variables of the final AR-model to an OLS-model to obtain residuals before autoregressive transformation ('untransformed residual'). Then, we explored the autocorrelation pattern of the residuals by estimating the autocorrelation function (ACF) and the partial autocorrelation function (PACF).

3.5.7 Multivariable ordinary least squares regression analysis

A 'naive model', ignoring potential autocorrelation, was created using ordinary least squares regression analysis. The same strategies were applied for model building and model diagnostics as described above but without including any autoregressive terms.

Statistical analyses were performed in SAS for Windows (Version 9.1) and graphics were produced in R for Windows (Version 2.3.1) or Excel (Version 2003).

Chapter 4 Results

4.1 Farm A

4.1.1 General

The complete dataset consisted of 175 study weeks between 20 December 2000 and 14 April 2004. Prospective data collection started in study week 123. In study week 98, no batch of pigs was weaned (‘missing observation’). Data from study weeks 164 to 175 (n = 12) were excluded because of a change in weaning management. Additionally, data from the previous 23 study weeks (week 141 to 163) were excluded due to the occurrence of multiple missing values in weight measurements. Consequently, the dataset used for analysis included 139 batches weaned weekly between 20 December 2000 and 20 August 2003 (33 months).

4.1.2 Descriptive analysis

4.1.2.1 <u>Overall</u>

Table 4.1.1 summarizes descriptive statistics of variables and significance values for time effects (year, season, year x season). A year effect was significant for all variables apart from most breeding herd parameters, grower and finisher mortality rates and two feed intake parameters. In addition, a seasonal effect was found for all weight measurements (apart from ‘Weaning weight’), ‘Weaning age’, feed intake parameters (apart from ‘finisher diet 2’), ‘Days to market’ and ‘Market weight’. A seasonal effect was also present for pre-weaning and weaner mortality rate.

Table 4.1.1. Descriptive statistics for performance parameters of 139 batches of pigs weaned weekly between 20 December 2000 and 20 August 2003 on farm A. The effects of year and season were investigated as main and interaction effects (Year x Season) using Analysis of Variance (ANOVA). Effects not significant at $P = 0.05$ are denoted by NS.

Variable type	Variable	n	Mean (SD)	Median	Q1, Q3	Missing	P-value		
							Year	Season	Season x Year
Discrete variables									
	Entry numbers	139	159.3 (4.1)	160	158, 162	0	<0.001	<0.001	<0.001
	Median number of piglets weaned per sow	139	10.0 (0.6)	10	10, 10	0	NS	0.04	NS
	Median parity of sows weaned (excl. gilts)	139	4.4 (1.0)	4.5	4.0, 5.0	0	NS	0.04	NS
Percentages									
	Pre-weaning mortality rate (%)	139	11.4 (4.1)	10.8	7.9, 14.2	0	<0.001	0.007	NS
	Coefficient of variation in weaning age (%)	139	8.6 (4.8)	7.6	5.3, 10.2	0	NS	NS	NS
	Percentage of gilts farrowed (%)	139	16.6 (9.3)	16.7	11.1, 23.1	0	NS	NS	NS
	Percentage of pigs weaned directly (%)	139	74.1 (24.6)	78.6	56.5, 92.4	0	0.001	<0.001	0.001
	Weaner mortality rate (%)	139	1.1 (1.3)	0.6	0.0, 1.6	0	0.004	NS	NS
	Grower mortality rate (%)	139	0.2 (0.4)	0.0	0.0, 0.6	0	NS	NS	NS
	Finisher mortality rate (%)	139	0.6 (0.7)	0.6	0.0, 1.2	0	NS	NS	NS
	Overall mortality rate (%)	139	1.9 (1.5)	1.9	0.6, 2.7	0	0.02	NS	NS
Continuous variables									
	Weaning age (d)	139	33.6 (0.9)	34.0	33.0, 34.0	0	0.007	0.002	NS
	Weaning weight (WWGT) (kg)	134	9.3 (0.9)	9.3	8.7, 9.8	5	<0.001	NS	NS
	Weight of pigs from special rearing location (TWGT) (kg)	114	9.2 (1.4)	9.5	8.2, 10.2	25	<0.001	0.002	<0.001
	Overall entry weight = WGT 1 (kg)	139	9.3 (0.9)	9.3	8.7, 9.9	0	<0.001	0.04	<0.001
	WGT 2 at 30 days post-weaning (kg)	125	22.7 (1.8)	22.7	21.5, 23.9	14	0.001	0.03	NS
	WGT 3 at 48 days post-weaning (kg)	139	37.1 (3.2)	37.1	34.9, 39.4	0	<0.001	0.01	NS
	WGT 4 at 62 days post-weaning (kg)	135	49.1 (3.9)	49.1	46.2, 52.1	4	<0.001	<0.001	0.008
	WGT 5 at 76 days post-weaning (kg)	132	60.5 (4.5)	60.6	57.1, 63.4	7	<0.001	0.01	NS
	Growth rate from WGT 3 to WGT 5 (g/d)	132	835 (91)	838	776, 890	7	<0.001	0.04	NS
	Days to market (d)	139	111.9 (3.3)	111.5	110.3, 112.7	0	<0.001	<0.001	<0.001

Variable type	Variable	n	Mean (SD)	Median	Q1, Q3	Missing	P-value		
							Year	Season	Season x Year
	Carcass weight at market (kg)	139	65.3 (3.2)	64.9	63.0, 67.2	0	0.01	0.002	0.02
	Daily feed intake weaner diet (kg/d)	136	0.156 (0.047)	0.153	0.115, 0.185	3	0.002	0.02	0.002
	Daily feed intake grower diet (kg/d)	139	0.722 (0.182)	0.700	0.616, 0.762	0	NS	0.04	NS
	Daily feed intake finisher diet 1 (kg/d)	122	1.851 (0.299)	1.781	1.680, 1.955	17	0.007	0.01	NS
	Daily feed intake finisher diet 2 (kg/d)	131	2.189 (0.242)	2.183	2.073, 2.300	8	NS	NS	NS

WGT: Sample weight.

4.1.2.2 Missing values

Missing values for 'Weaning weight' (WWGT, n = 5) and for 'Weight of pigs from special rearing location' (TWGT, n = 25) were not considered as missing as presumably no pigs from either of these two sub-populations entered a batch. Amongst the remaining variables, missing values occurred in three weight (prevalence: 2.9 to 10.1%) and three feed parameters (prevalence: 2.2 to 12.2%).

The missing value pattern (Figure 4.1.1) indicated neither a strong clustering in time of individual variables nor a dependency of missing values between variables of the same observation. Only missing values for 'Daily feed intake of diet 3' (DIET3) and 'Daily feed intake of diet 4' (DIET4) tended to be clustered at the beginning of the study period. All missing predictor variables were imputed by the value of the closest valid (generally preceding) measurement ('nearest neighbour imputation').

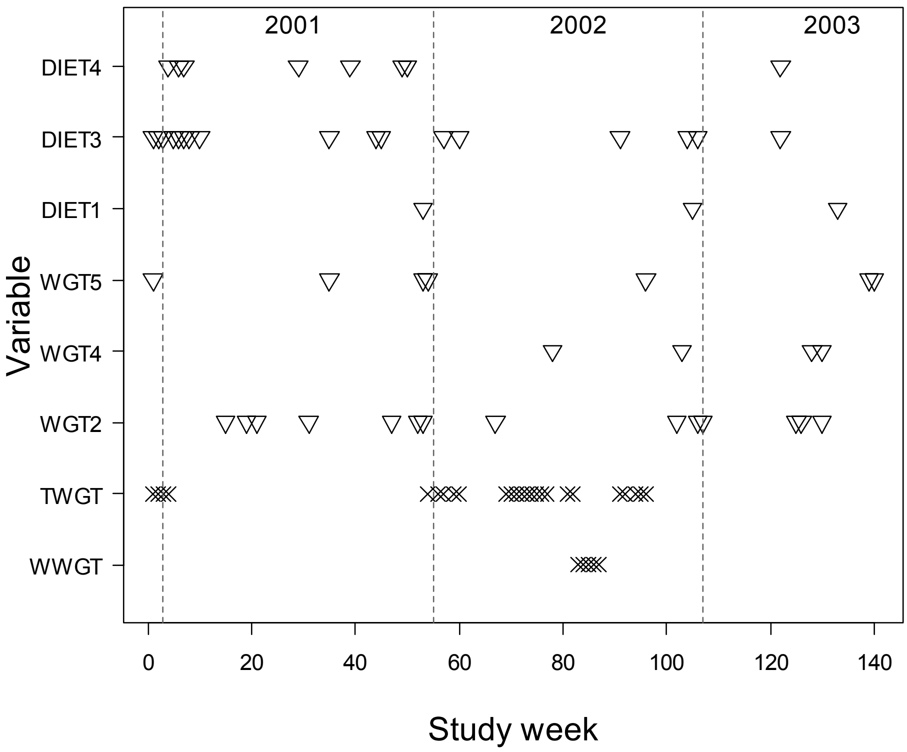

Figure 4.1.1. Missing value pattern of selected variables on pig farm A. Study week identifies batches (n = 139) weaned weekly between 20 December 2000 and 20 August 2003. Dashed lines separate subsequent years. WWGT: Weaning weight; TWGT: Weight of pigs from special rearing location; WGT: Sample weight (number indicates type of sample weight: 2 at 30 days, 4 at 62 days, 5 at 76 days post-weaning); DIET: Daily feed intake (number indicates number of diet, e.g. diet 1, 3 or 4). WWGT and TWGT have different markers (crosses) since they were not considered as true missing (see text).

4.1.2.3 Breeding herd parameters

The only breeding herd parameter showing a level shift over the years was 'Pre-weaning mortality' (Figure 4.1.2), which tended to increase since 2002. All other parameters were relatively stable over time. In particular, 'Weaning age' was highly consistent over the study period (median: 34 days, IQR: 33 to 34 days).

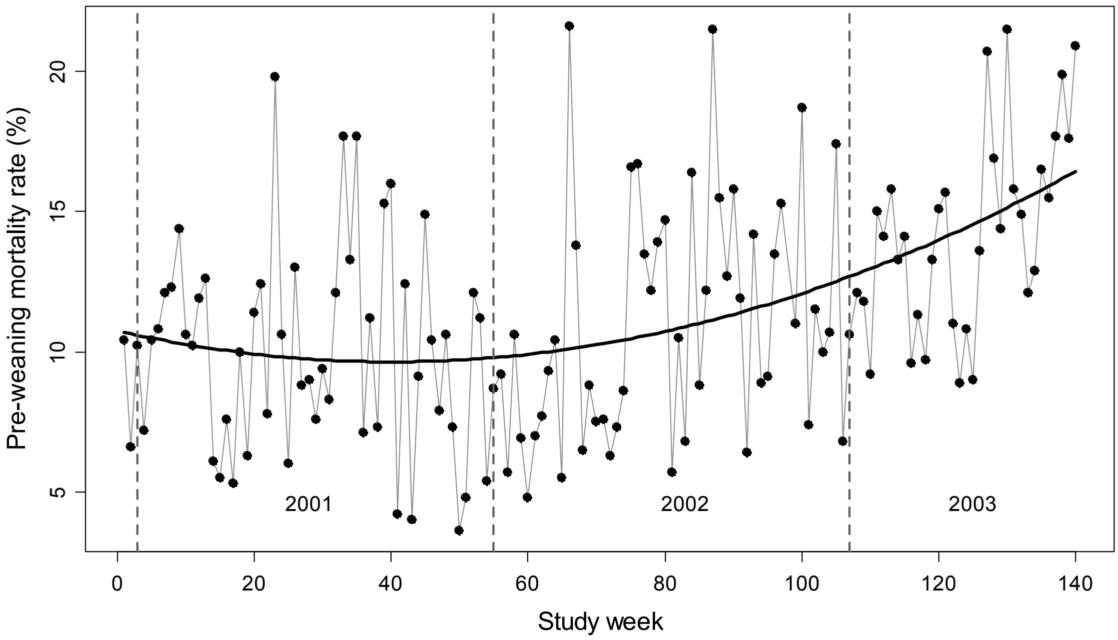

Figure 4.1.2. Time series plot of 'Pre-weaning mortality rate' on pig farm A. Study week identifies batches (n = 139) weaned weekly between 20 December 2000 and 20 August 2003. Black line illustrates a fitted quadratic trend line (F = 19.6, DF = 2, P < 0.001). Dashed lines separate subsequent years.

4.1.2.4 Entry parameters

A median number of 160 pigs (IQR: 158 to 162 pigs) entered a batch (Figure 4.1.3). Batches with overall entry numbers below 160 pigs (n = 39) were clustered in 2002 (n = 31).

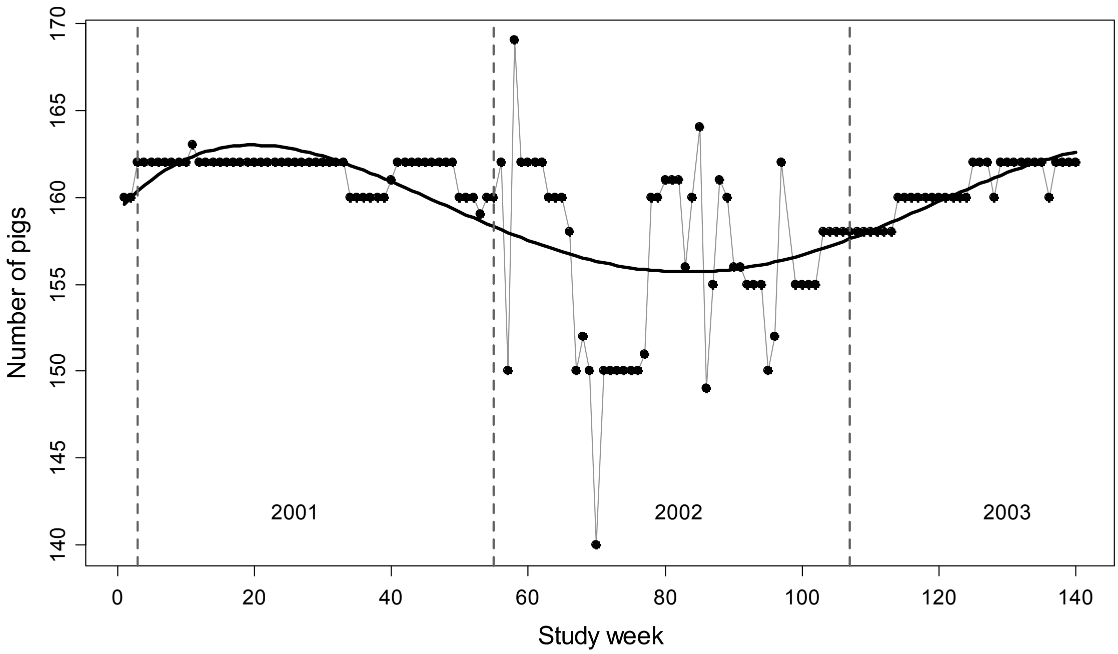

Figure 4.1.3. Time series plot of number of pigs entering batches weaned weekly on pig farm A. Study week identifies batches (n = 139) weaned weekly between 20 December 2000 and 20 August 2003. Black line illustrates a fitted 4th order polynomial trend line ($F = 20.64$, $DF = 4$, $P < 0.001$). Dashed lines separate subsequent years.

The 'Percentage of pigs weaned directly' was 100% for 25 batches and 0% for 5 batches. This parameter showed a level shift between years (Figure 4.1.4) with median levels of 56%, 93% and 76% in 2001, 2002 and 2003, respectively.

Although the exact age of piglets from the special rearing location (SRL) was not known, it was assumed that pigs stayed in the SRL for an approximate period of one week. This results in an estimated overall entry age of 35.8 d given that 75% of the batch was weaned directly. Records for piglets entering the SRL and for piglets being moved out from the SRL were available for 110 and 114 study weeks, respectively. A median number of 48 piglets (IQR: 24 to 75 piglets) was moved onto the SRL. Move in- and move out weights for the SRL were significantly affected by year (Table 4.1.2). The difference between recorded move-in and move-out weights was 3.2 kg in 2001, 2.2 kg in 2002 and 2.6 kg in 2003. These values result in 7-day growth rates of 460 g/d, 310 g/d and 370 g/d in 2001, 2002 and 2003, respectively.

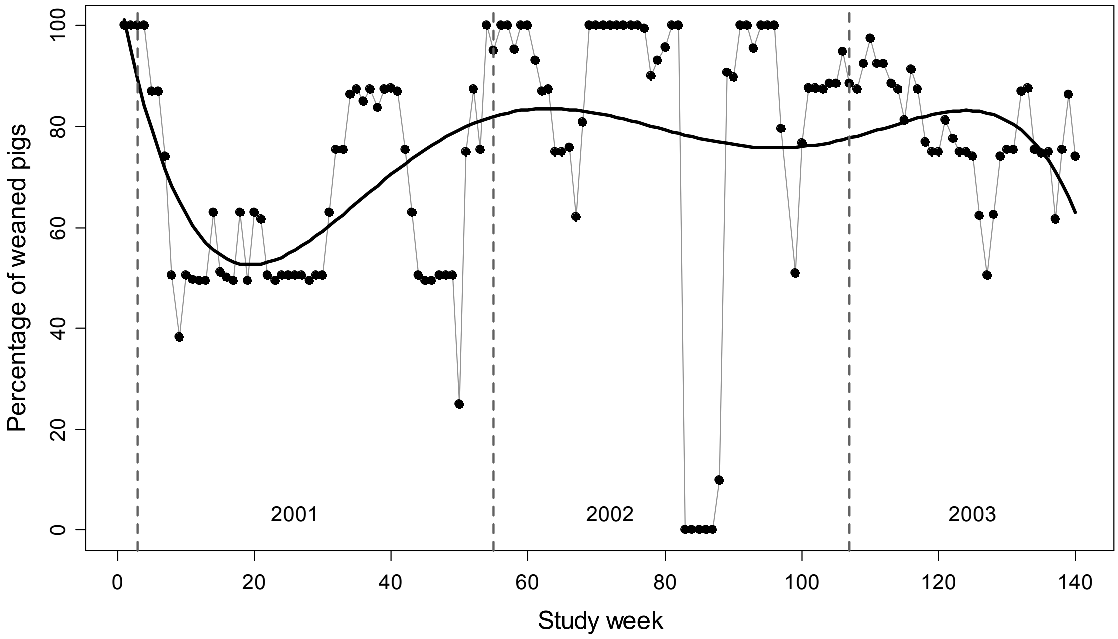

Figure 4.1.4. Time series plot of 'Percentage of piglets weaned directly' for batches weaned weekly on pig farm A. Study week identifies batches (n = 139) weaned weekly between 20 December 2000 and 20 August 2003. Black line illustrates a fitted 5th order polynomial trend line (F = 17.80, DF = 5, P < 0.001). Dashed lines separate subsequent years.

Table 4.1.2. Median weight (Q1, Q3: Interquartile range) of pigs entering ('Move-in weight') and leaving the special rearing location ('Move-out weight') stratified by year. The effect of year was highly significant for both parameters (P < 0.001) resulting in given parameter estimates ('Beta') and standard errors ('SE'). The number of study weeks with available records is indicated by n.

Year	Move in weight (kg)				Move out weight (kg)			
	n	Median (Q1, Q3)	Beta	SE	n	Median (Q1, Q3)	b	SE
2001	50	6.9 (6.4, 7.2)	REF		49	10.1 (9.6, 10.5)	REF	
2002	27	6.4 (5.8, 7.4)	-0.23	0.21	31	8.6 (7.8, 9.3)	-1.50	0.28
2003	33	5.8 (5.5, 6.2)	-0.98	0.20	34	8.4 (7.6, 10.1)	-1.32	0.27
Total	**110**	**-**	**-**	**-**	**114**	**-**	**-**	**-**

4.1.2.5 Deaths and sick pig movements

In total, 497 deaths were recorded, of which 55.2% died at the weaner stage, 11.0% at the grower stage, and 33.8% at the finisher stage. Figure 4.1.5 indicates a cluster of high weaner mortality rate in 2002. 'Overall mortality rate' showed a cluster of high values over a similar period. No trend was significant in grower and finisher mortality rate.

In 63.0% of the batches, a median number of two pigs (range: 1 to 9) was moved to the hospital pen (total number of pigs: 190). The median age of pigs moved to the hospital pen was 64.4 days (range: 0 to 119 days). Exact weight measurements for those pigs were not available.

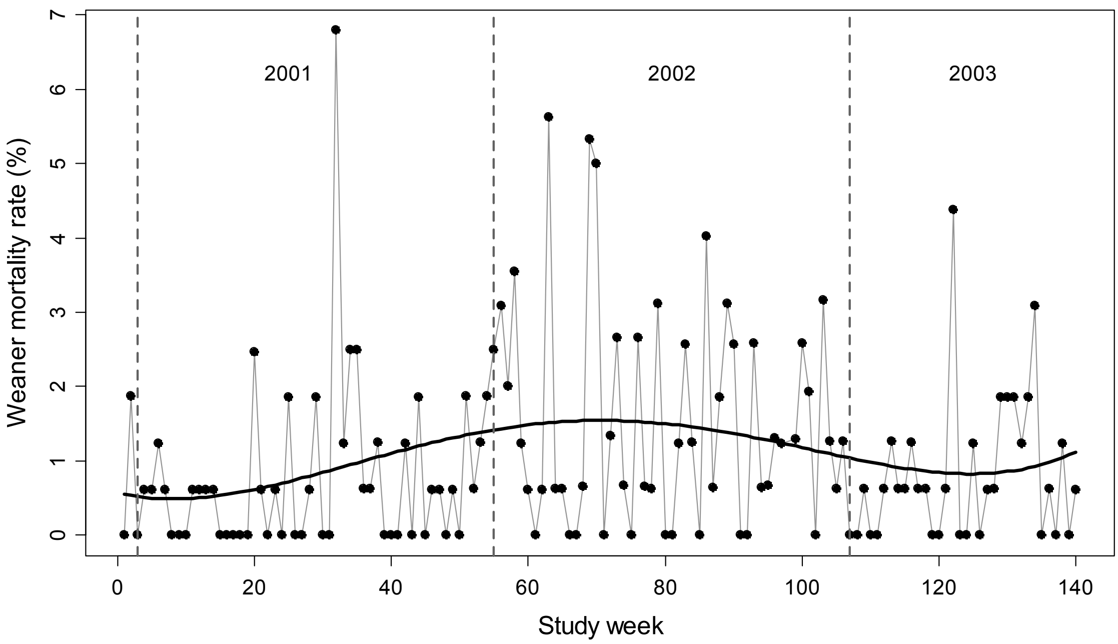

Figure 4.1.5. Time series plot of 'Weaner mortality rate' of batches weaned weekly on pig farm A. Study week identifies batches (n = 139) weaned weekly between 20 December 2000 and 20 August 2003. Black line illustrates a fitted 4th order polynomial trend line (F = 2.51, DF = 4, P = 0.04). Dashed lines separate subsequent years.

4.1.2.6 Unaccounted pigs

Unaccounted pigs occurred in 111 batches after accounting for deaths, transfers and marketing events. The median number of unaccounted pigs was 1 (range: -6 to 12). In total 269 more pigs were moved in than moved out (+269 unaccounted pigs) and 19 less pigs were moved in than moved out (-19 unaccounted pigs). The highest frequency of positive unaccounted pigs (n = 127) occurred in 2002 accounting for 47.2% of all positive unaccounted pigs.

Since pigs were not counted at transfer to the grower shed, unaccounted pigs could only be assessed for the combined weaner and grower stage. More positive unaccounted pigs (n = 160) occurred at the weaner/grower stage than at the finisher stage (n = 109). The number of negative unaccounted pigs was similar between the weaner/grower (n = 9) and the finisher stage (n = 10).

4.1.2.7 Sample weights

Initial validation of sample weight records resulted in the exclusion of eight records (two double records, four sample weights recorded at non-routine weighing dates and two records with insensible, low weights).

The percentage of pigs weighed within a batch was 100% at weaning (WGT 1), 25.0% (IQR: 24.7 – 25.5%) at the grower stage (WGT 2), and 9.5% (IQR: 9.3% - 10.0%) at the finisher stage (WGT 3 to WGT 5). Pigs from sample pens weighed 22.7 kg, 37.1 kg, 49.1 kg and 60.6 kg at 30 days (WGT 2), 48 days (WGT 3), 62 days (WGT 4) and 76 days (WGT 5) post-weaning, respectively. In the following, only WGT 2, WGT 3 and 'Growth rate WGT 3 to WGT 5' will be presented as WGT 3, WGT 4 and WGT 5 were repeated measurements on the same sample pens. The finisher growth rate from 48 days post-weaning to market was 782 g/d.

Batch-specific growth curves from weaning to 76 days post-weaning stratified by 6-month periods are displayed in Figure 4.1.6. In the stratum 'July 02 to Dec 02', eight batches were weighed one week after the routine weighing days compared to the remaining batches. The same stratum included the five batches with no pigs being recorded as weaned directly (weaning weight missing). In general, batches with initially low weights had subsequently low sample weights. In some strata, the curves tended to flatten towards the end of the displayed curves.

Overall entry weight (WGT 1) decreased in 2002 and increased thereafter (Figure 4.1.7). Between study week 33 and 69, WGT 1 showed high serially dependent variability. Within those 26 weeks, this parameter fluctuated between subsequent extremes of 7.4 kg, 12.0 kg, 8.5 kg and 10.8 kg, after which it expressed a more regular pattern again. A similar variability was also seen in 'Carcass weight' (Figure 4.1.12). The median difference between move-in weights of piglets from the SRL (TWGT) and move-in weights of directly weaned piglets (WWGT) was negligible (median: -0.09 kg, IQR: -1.01 to +0.57 kg).

All other weight measurements showed a linear downward trend. The respective fitted linear regression line predicted a weekly decline in WGT 2 (Figure 4.1.8) by 13.1 g (SE ± 3.8 g), in WGT 3 (Figure 4.1.9) by 24.8 g (SE ± 6.5 g) and in daily 'Growth rate WGT 3 to WGT 5' (Figure 4.1.10) by 0.85 g/d (SE ± 0.19 g/d).

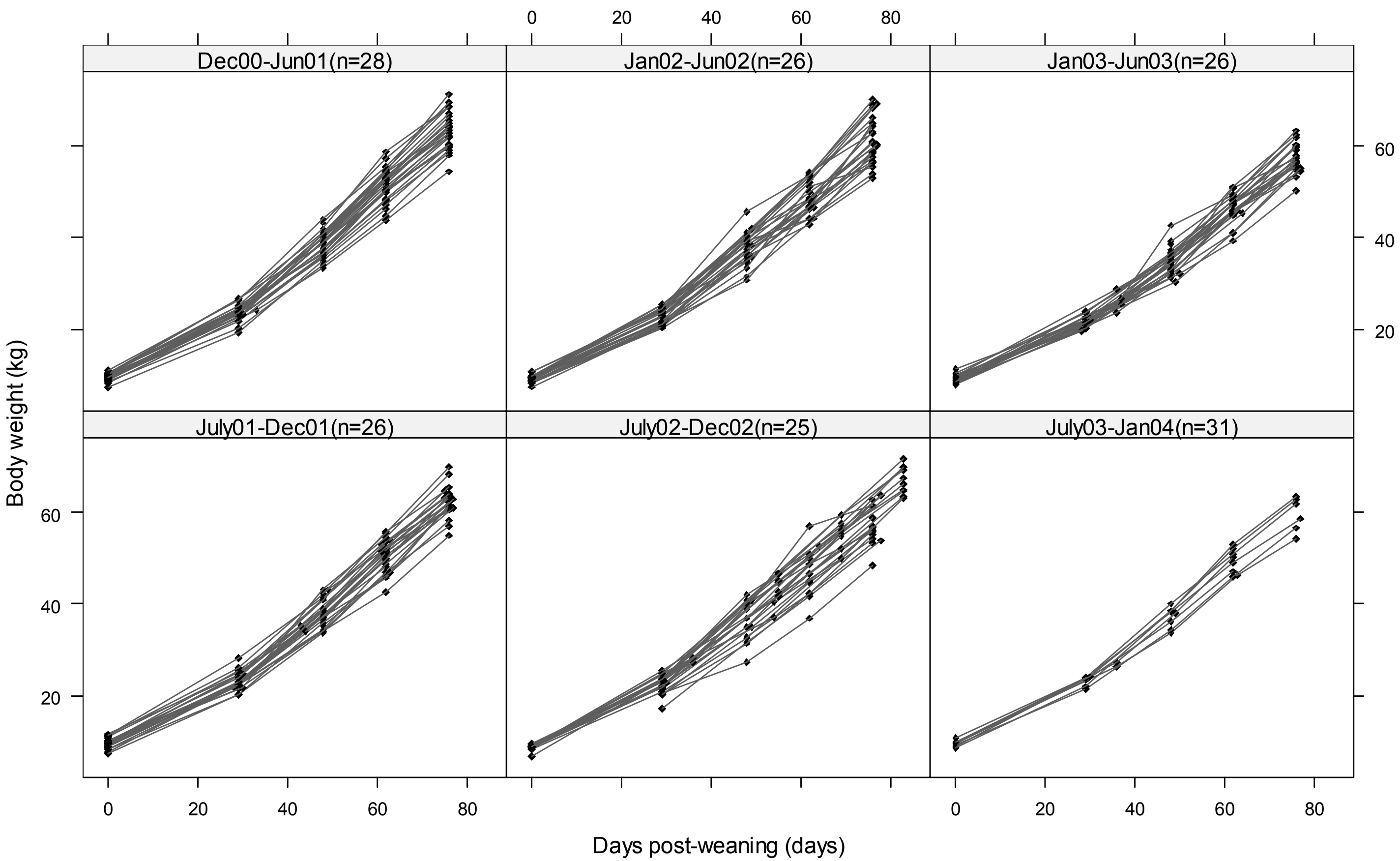

Figure 4.1.6. Batch-specific growth curves from weaning until the last sample weight measurement at 78 days post-weaning on pig farm A. Study week identifies batches (n = 139) weaned weekly between 20 December 2000 and 20 August 2003. Batches were stratified by approximate six-month periods.

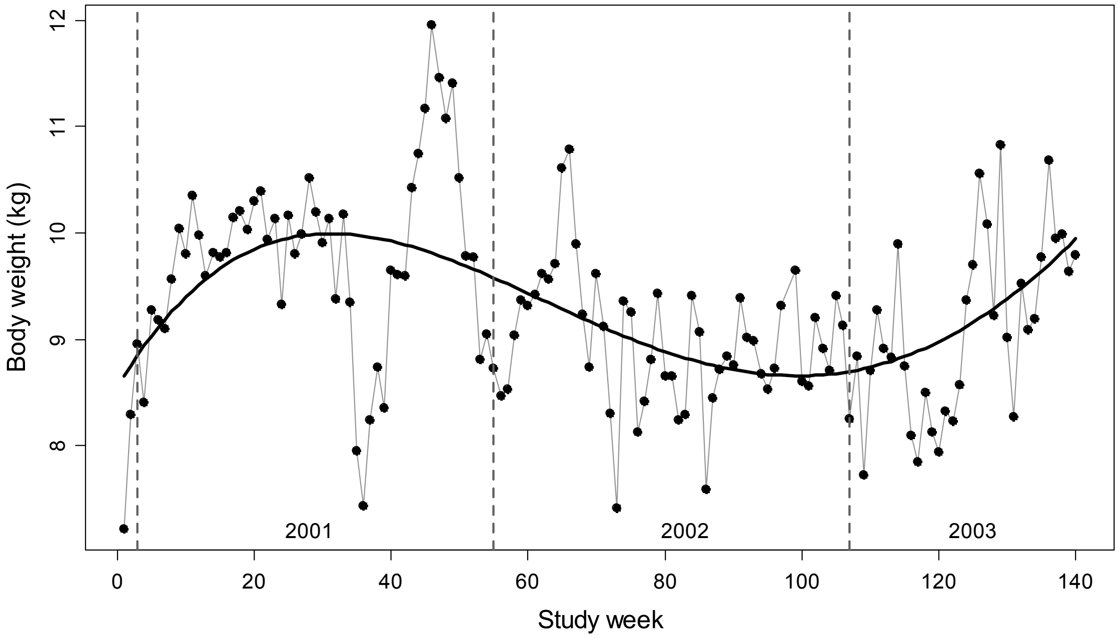

Figure 4.1.7. Time series plot of 'Sample weight 1' (day 0 post-weaning) of batches weaned weekly on pig farm A. Study week identifies batches (n = 139) weaned weekly between 20 December 2000 and 20 August 2003. Black line illustrates a fitted 4th order polynomial trend line ($F = 13.17$, $DF = 4$, $P < 0.001$). Dashed lines separate subsequent years.

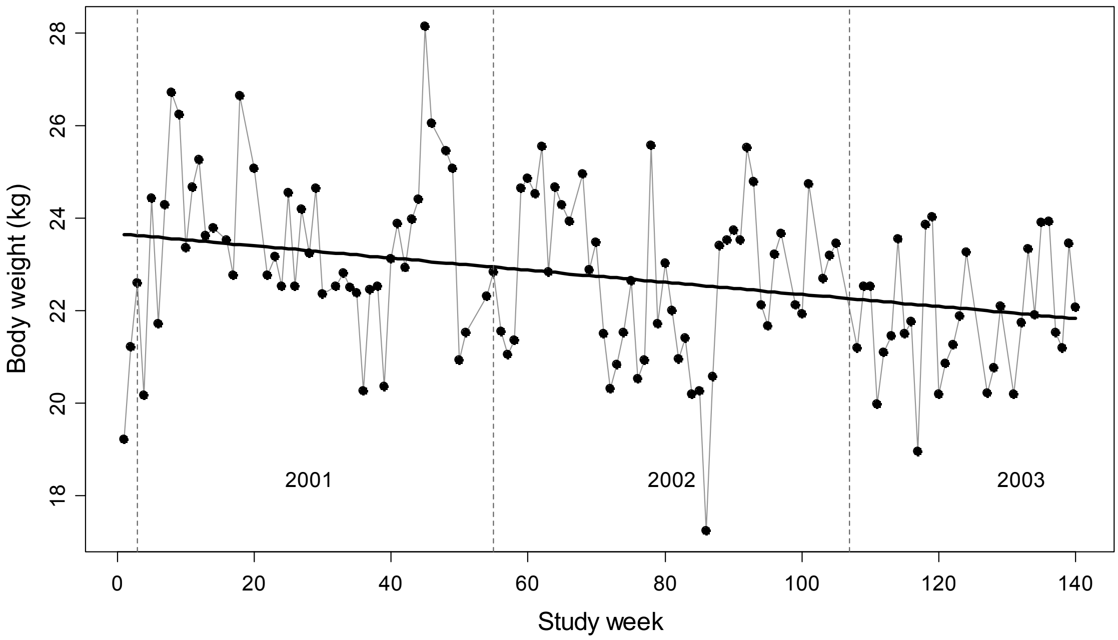

Figure 4.1.8. Time series plot of 'Sample weight 2' (day 30 post-weaning) on pig farm A. Study week identifies batches (n = 125) weaned weekly between 20 December 2000 and 20 August 2003. Black line indicates a linear trend line ($F = 11.18$, $DF = 1$, $P = 0.001$). Dashed lines separate subsequent years.

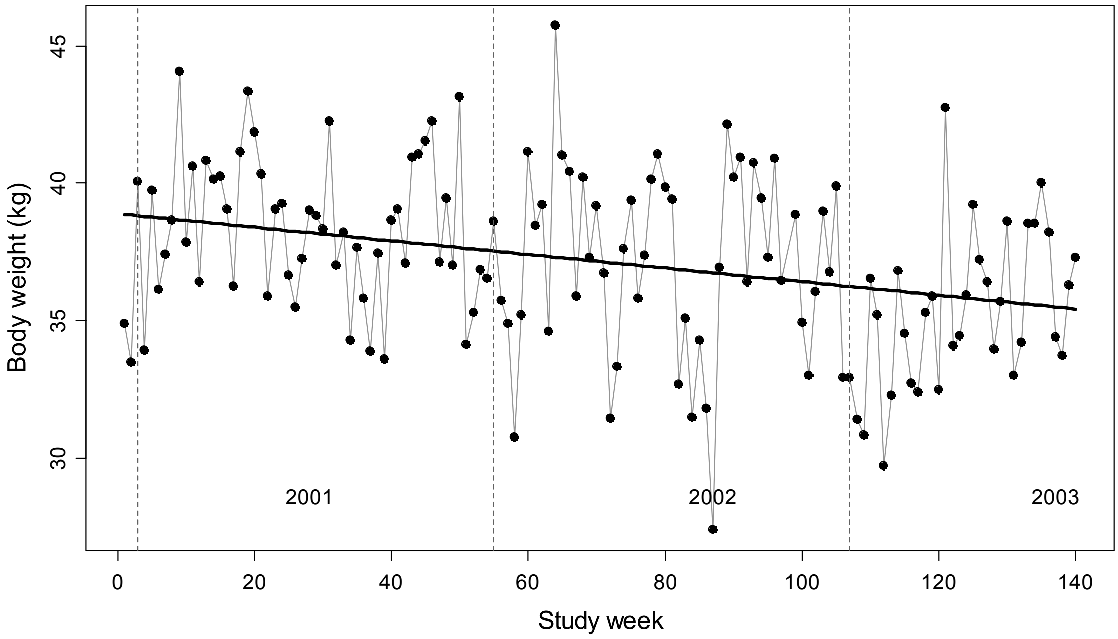

Figure 4.1.9. Time series plot of 'Sample weight 3' (day 48 post-weaning) on pig farm A. Study week identifies batches (n = 139) weaned weekly between 20 December 2000 and 20 August 2003. Black line illustrates a fitted linear trend line (F = 20.35, DF = 1, P < 0.001). Dashed lines separate subsequent years.

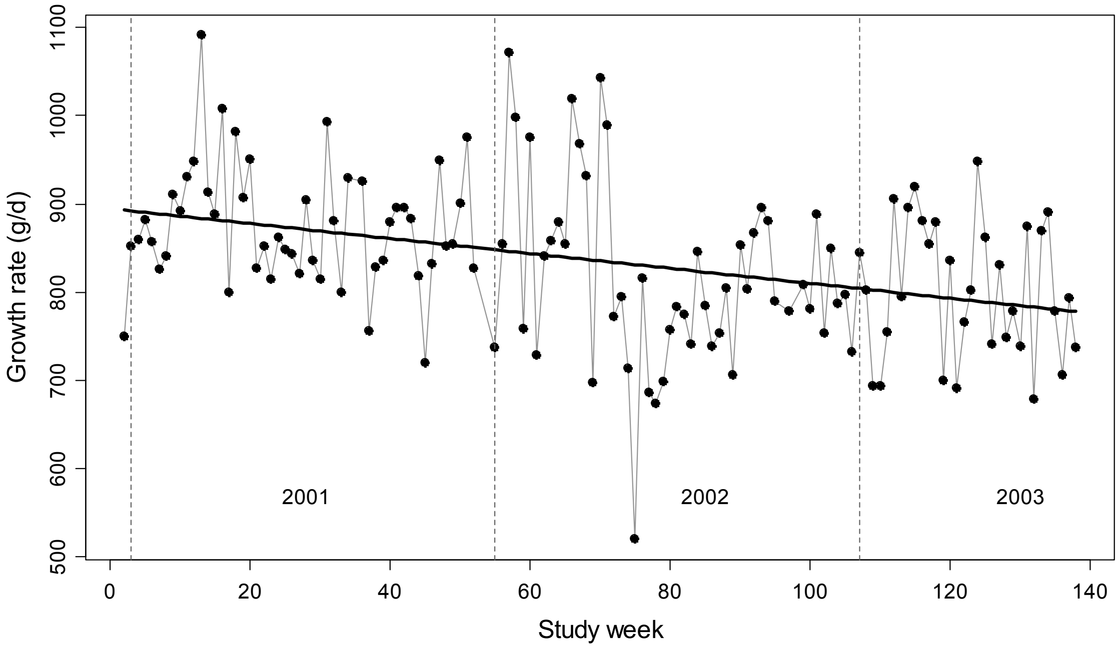

Figure 4.1.10. Time series plot of daily growth rate during the first four weeks of the finisher stage (day 48 to 76 post-weaning) on pig farm A. Study week identifies batches (n = 132) weaned weekly between 20 December 2000 and 20 August 2003. Black line illustrates a fitted linear trend line (F = 20.87, DF = 1, P < 0.001). Dashed lines separate subsequent years.

4.1.2.8 Market parameters

A total number of 21,470 pigs was recorded as sold, of which 222 pigs (1.0%) were sold privately. Pigs sold privately were weighed on-farm (live weight records), hence having live weight records only. 'Carcass weight' for these pigs was calculated using a standard killing-out percentage curve (Equation 3.1). For the remaining pigs, 'Carcass weight' of the marketing batch was the only available measure for final market weight. A marketing batch included individual pigs from one age group (57%), two age groups (42%) or three age groups (1%). If a marketing batch included pigs from more than one age group, a median percentage of 89% (range: 56 to 99%, IQR: 85.3 to 93.3%) was sold from the predominant age group (Figure 4.1.11).

A level shift occurred for numbers of pigs sold per batch, with a median level of 158 pigs (IQR: 156 to 160 pigs) in 2001, 151 pigs (IQR: 147 to 154 pigs) in 2002 and 156 pigs (IQR: 154 to 157 pigs) in 2003.

Pigs were marketed at a mean time of 111.9 days post-weaning at 65.3 kg, which corresponds with a live weight of 87.1 kg (assumed dressing percentage: 75%). These values result in a mean daily growth rate from birth to market live weight of 581 g/d (estimated entry age: 35.4 d). Strong peaks of 'Carcass weight' (Figure 4.1.12) corresponded closely with peaks of 'Days to market' (Figure 4.1.13). In contrast to the long-term upward trend in 'Days to market', 'Carcass weight' exhibited a significant downward trend ($P = 0.002$). The fitted linear trend line indicated that 'Carcass weight' decreased by 0.021 kg (SE $\pm$ 0.006 kg) per week.

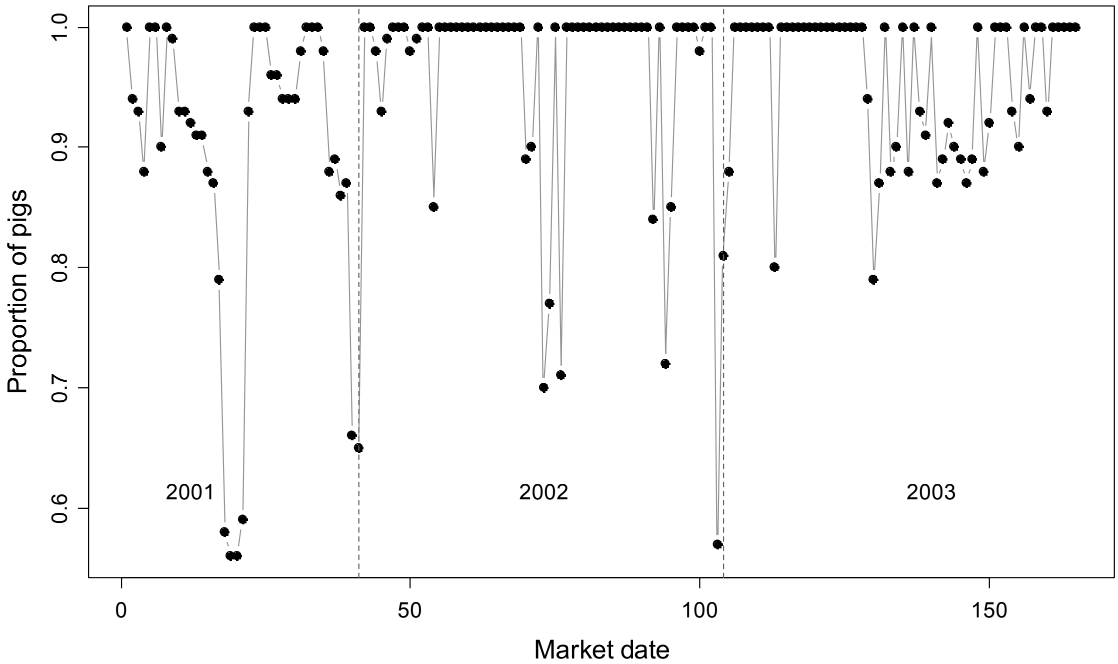

Figure 4.1.11. Time series plot of 'Proportion of pigs sold from predominant age group' for marketing batches (n = 165) sold between 22 March 2001 and 10 December 2003 from pig farm A. Dashed lines separate subsequent years.

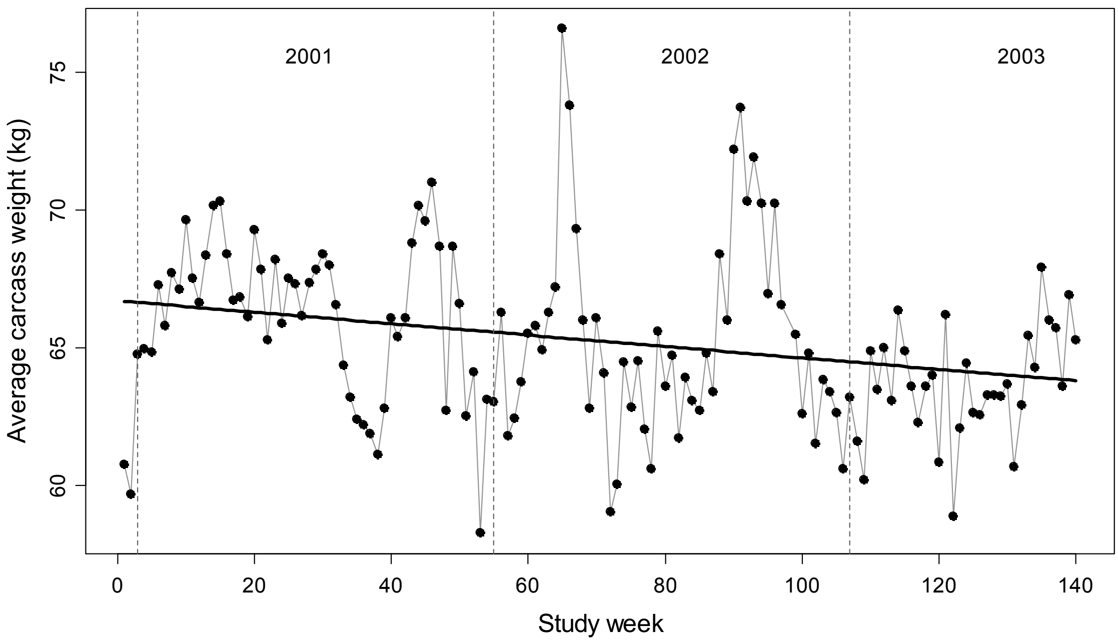

Figure 4.1.12. Time series plot of 'Carcass weight' of grower batches on pig farm A. Study week identifies batches (n = 139) weaned weekly between 20 December 2000 and 20 August 2003. Black line illustrates a fitted linear trend line (F = 10.36, DF = 1, P = 0.002). Dashed lines separate subsequent years.

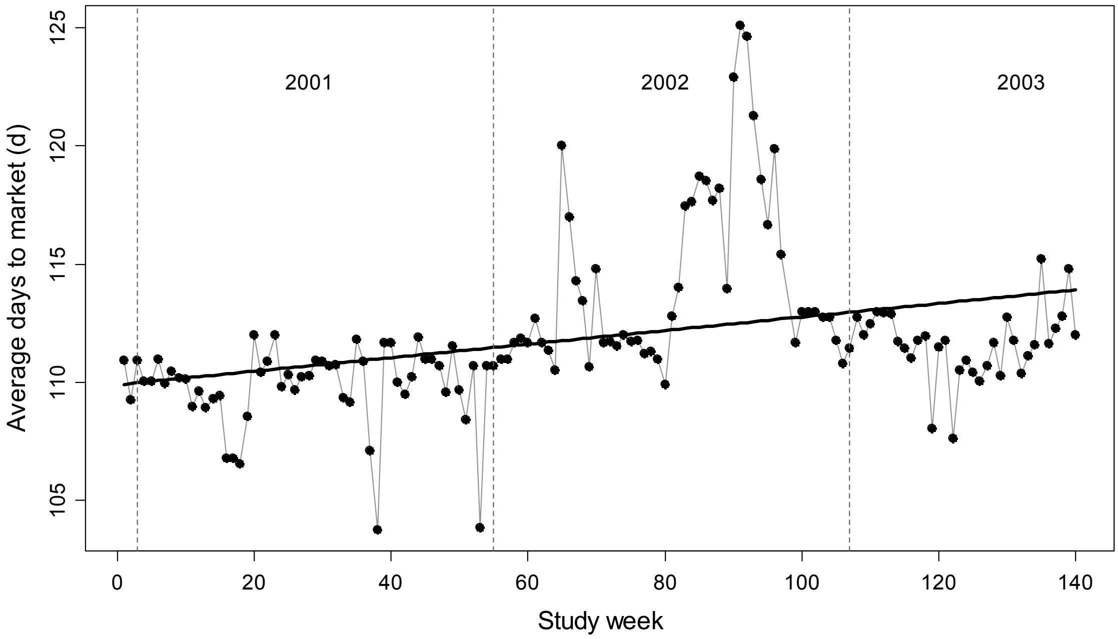

Figure 4.1.13. Time series plot of 'Days to market' of grower batches on pig farm A. Study week identifies batches (n = 139) weaned weekly between 20 December 2000 and 20 August 2003. Black line illustrates a fitted linear trend line (F = 19.24, DF = 1, P < 0.001). Dashed lines separate subsequent years.

4.1.2.9 Feed parameters

Median daily feed intake was 0.153 kg/d, 0.700 kg/d, 1.781 kg/d and 2.183 kg/d for diets 1, 2, 3 and 4, respectively. 'Daily feed intake diet 1' (Figure 4.1.14) varied considerably within and between years. A highly variable period with strong serial correlation occurred between study week 32 and 91. No significant trend was detected for 'Daily feed intake diet 2' (Figure 4.1.15) and 'Daily feed intake diet 4' (Figure 4.1.17). However, both graphs indicate several outliers. 'Daily feed intake diet 3' showed a moderate increase over time (Figure 4.1.16).

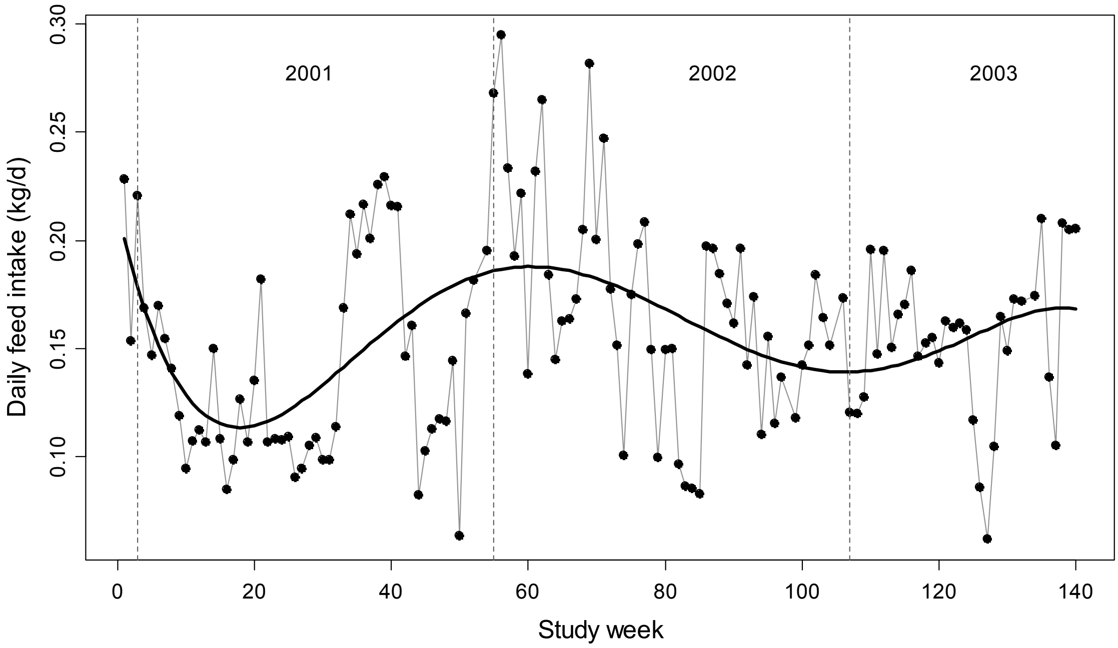

Figure 4.1.14. Time series plot of ‘Daily feed intake diet 1’ (day 0 to 23 post-weaning) on pig farm A. Study week identifies batches (n = 136) weaned weekly between 20 December 2000 and 20 August 2003. Black line illustrates a fitted 5th order polynomial trend line ($F = 7.16$, $DF = 5$, $P < 0.001$). Dashed lines separate subsequent years.

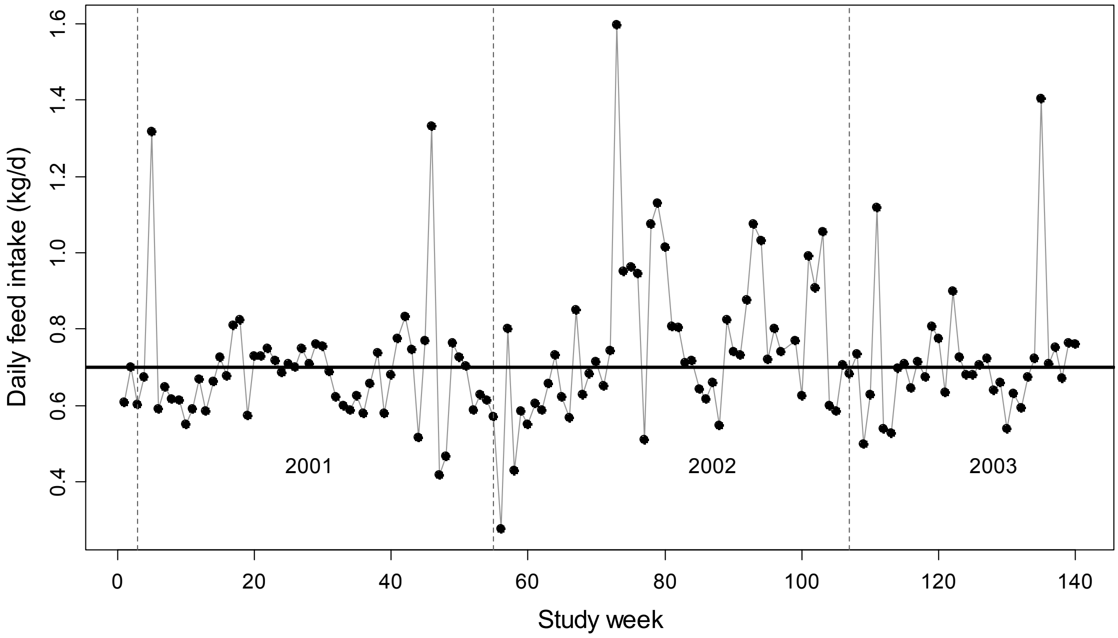

Figure 4.1.15. Time series plot of ‘Daily feed intake diet 2’ (day 23 to 48 post-weaning) on pig farm A. Study week identifies batches (n = 139) weaned weekly between 20 December 2000 and 20 August 2003. Black line illustrates the median level of ‘Daily feed intake diet 2’. Dashed lines separate subsequent years.

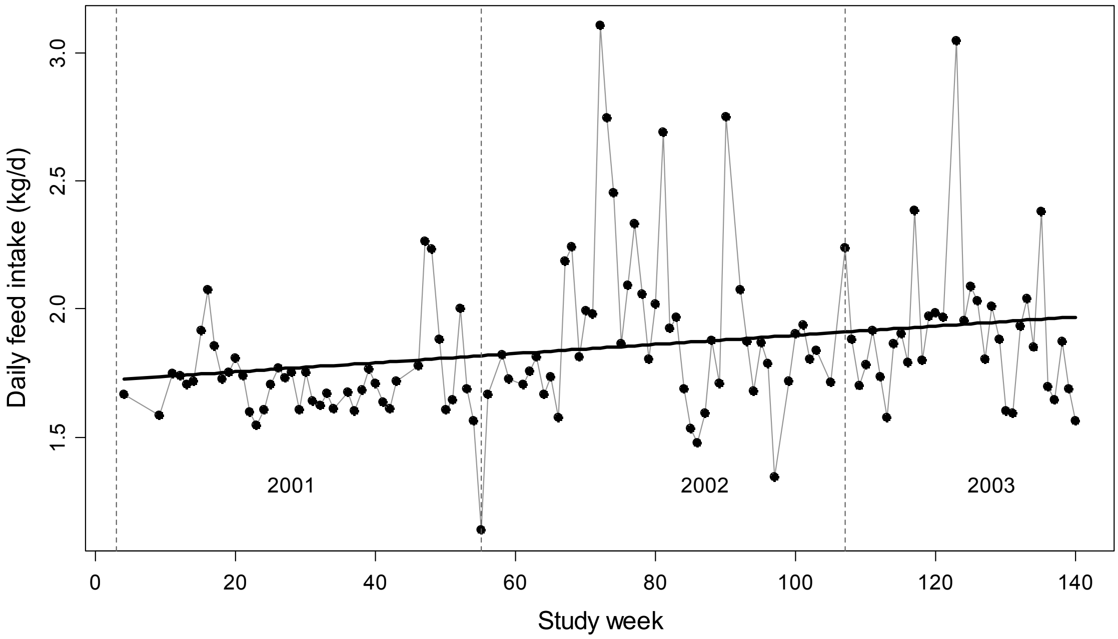

Figure 4.1.16. Time series plot of ‘Daily feed intake diet 3’ (day 48 to 62 post-weaning) on pig farm A. Study week identifies batches (n = 122) weaned weekly between 20 December 2000 and 20 August 2003 Black line illustrates a fitted linear trend line (F = 6.87, DF = 1, P = 0.01). Dashed lines separate subsequent years.

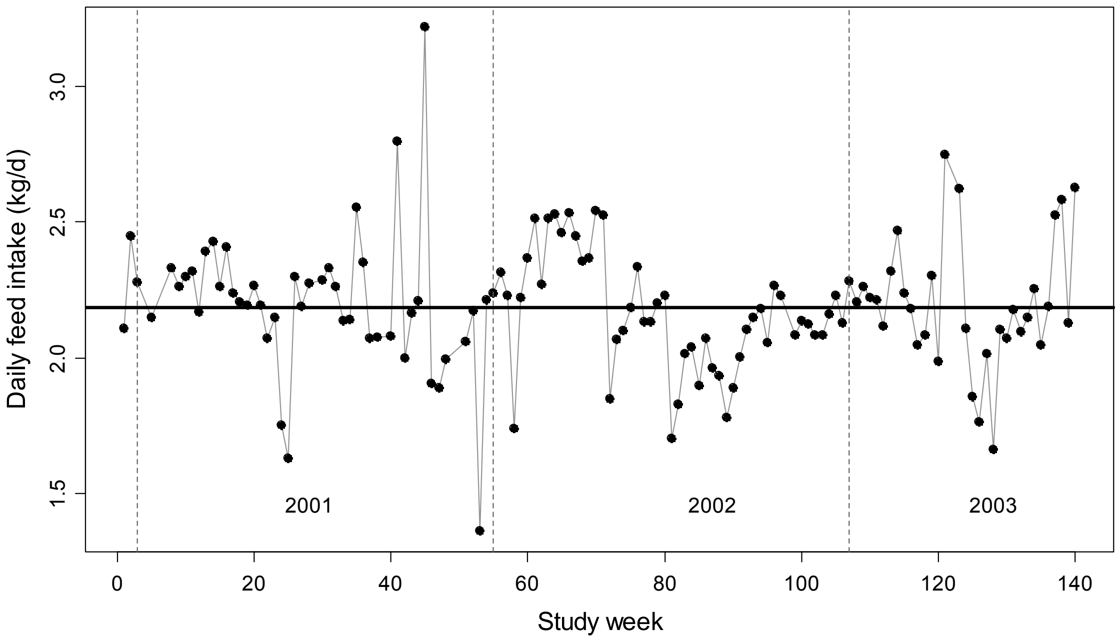

Figure 4.1.17. Time series plot of ‘Daily feed intake diet 4’ (day 62 post-weaning to market) on pig farm A. Study week identifies batches (n = 131) weaned weekly between 20 December 2000 and 20 August 2003. Black line illustrates the median level of ‘Daily feed intake diet 4’. Dashed lines separate subsequent years.

4.1.3 Univariable time series analysis

The autocorrelation function (ACF) for ‘Carcass weight’ slowly decayed, whilst the partial autocorrelation (PACF) dropped off after lag 2 (Figure 4.1.18) indicating a second-order autoregressive process with positive autocorrelation. In addition, the PACF indicated further lags with significant autocorrelation at lags 6, 7, 9 and 12.

We investigated the behaviour of the ACF and PACF after removing the linear trend (Figure 4.1.19) as the presence of a trend may bias autocorrelation estimates. Although lags with significant autocorrelation were similar, autocorrelation estimates of both, the ACF and PACF, were slightly lower for the detrended series. For the raw series, autocorrelations estimated by the ACF were overestimated by 0.093 (range: 0.036 to 0.126) compared to the detrended series. Similarly, the PACF for the raw series overestimated autocorrelations by 0.029 (range: 0.010 to 0.053).

As suspected from the ACF and PACF, backward elimination of autoregressive terms resulted in a first-order (AR1: -0.50 ± SE 0.08, $P < 0.001$) and second-order autoregressive term (AR2: -0.20 ± SE 0.08, $P = 0.02$). This model explained 40.3% of the total variance in carcass weight as indicated by the total R-square. Residuals of this univariable autoregressive model showed remaining positive autocorrelation at lag 5 ($P = 0.04$) and remaining negative autocorrelation at lags 7 ($P = 0.02$), 8 ($P < 0.001$), 12 ($P = 0.008$) and 13 ($P = 0.008$).

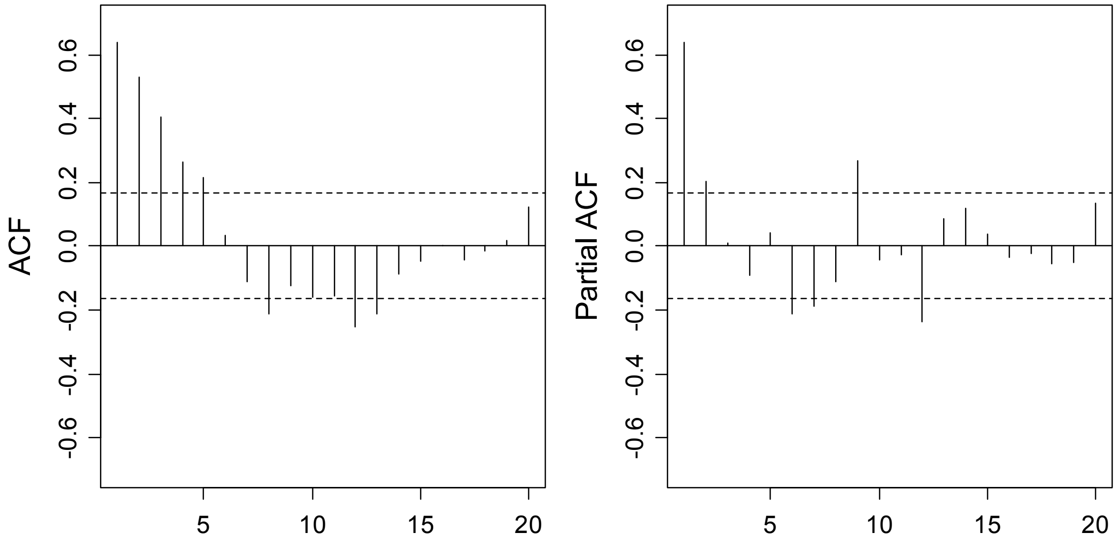

Figure 4.1.18. Autocorrelation function (ACF) and partial autocorrelation function (Partial ACF) of carcass weight of 139 batches of pigs weaned between 20 December 2000 and 20 August 2003 on farm A. One missing observation was imputed. Dashed lines indicate 5% significance level that autocorrelation is zero. The lag order is specified on the horizontal axis, whilst estimated autocorrelations are shown on the vertical axis.

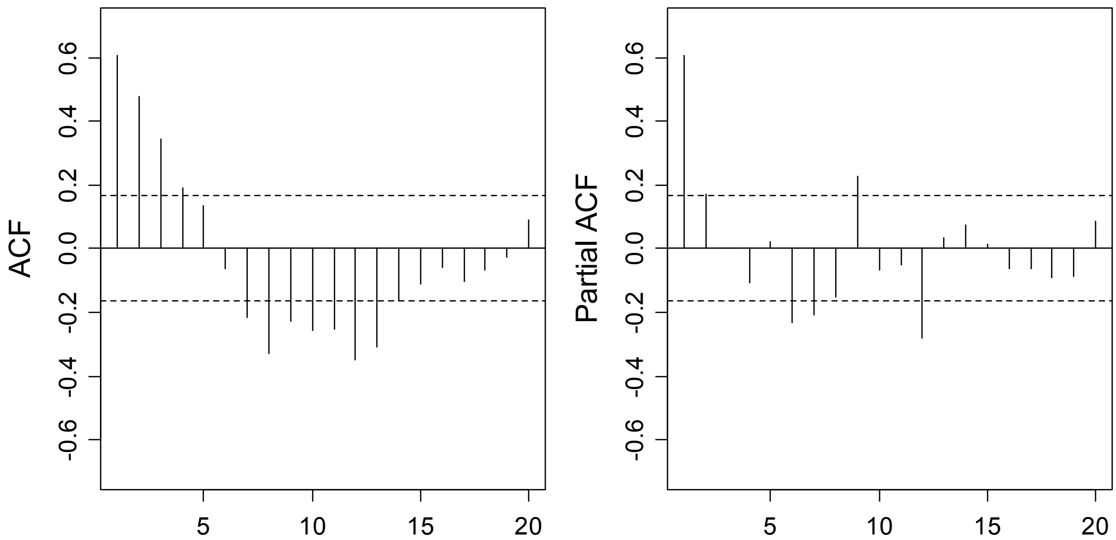

Figure 4.1.19. Autocorrelation function (ACF) and partial autocorrelation function (Partial ACF) for carcass weight after removal of the linear trend. Carcass weight was available for 139 batches of pigs weaned between 20 December 2000 and 20 August 2003 on farm A. One missing observation was imputed. Dashed lines indicate 5% significance level that autocorrelation is zero. The lag order is specified on the horizontal axis, whilst estimated autocorrelations are shown on the vertical axis.

4.1.4 Collinearity between predictor variables

‘Sample weight 3’ (WGT 3) was highly correlated with WGT 4 (r = 0.787) and WGT 5 (r = 0.809). Furthermore, ‘Weaner mortality rate’ was highly correlated with ‘Overall mortality rate’ (r = 0.819), and ‘Weaning weight’ was highly correlated with WGT 1 (r = 0.920). It was decided to include 'Growth rate WGT 3 to WGT 5' as a variable in the model, which showed low correlation with WGT 3 (r = 0.143). 'Weaner mortality rate' and WGT 1 were chosen from the other two pairs of highly correlated predictor variables due to their stronger associations with the outcome variable.

4.1.5 Univariable regression analysis with autoregressive error correction

Univariable analysis whilst adjusting for autocorrelation resulted in twelve parameters selected for multivariable analysis (Table 4.1.3). After correcting for second-order autocorrelation, season was significantly associated with carcass weight (P = 0.04), whereas the effect of 'Study week' was not significant (P = 0.37). WGT 1, WGT 3 and 'Days to market' showed strong positive associations with 'Carcass weight' (P < 0.001) producing 'Regression R^2'-values greater than 0.20.

Table 4.1.3. Predictor variables associated with market weight of 139 batches of pigs weaned between 20 December 2000 and 20 August 2003 on farm A. Variables were tested for associations using a second-order autoregressive model. The first- and second-order autoregressive terms were significant for all variables. Regression coefficients ('Beta') and their standard errors ('SE') are reported. The Regression R^2 (Regr. R^2) indicates the accuracy of the regression model after autoregressive transformation.

Variable	Category	Beta	SE	P-value	Regr. R^2
Days to market (d)		0.58	0.08	<0.001	0.29
WGT 3 (kg)		0.32	0.05	<0.001	0.21
WGT 1 (kg)		1.54	0.27	<0.001	0.20
Weaning age (d)		0.57	0.19	0.003	0.06
Location within shed	Outer pens	REF		0.005	0.06
	Middle pens	-0.99	0.35		
Percentage of gilts farrowed (%)		-0.042	0.016	0.009	0.05
WGT 2 (kg)		0.31	0.12	0.012	0.05
Season of weaning	Spring: Sep to Nov	REF		0.04	0.04
	Summer: Dec to Feb	-2.24	1.10		
	Autumn: Mar to May	-1.64	1.16		
	Winter: Jun to Aug	-2.17	1.08		
Growth rate WGT 3 to WGT 5 (g/d)		0.0035	0.0021	0.09	0.02
Daily feed intake finisher diet 2 (kg/d)		1.30	0.88	0.10	0.02
Finisher shed	Shed A	REF		0.10	0.02
	Shed B	0.70	0.42		
Median parity of sows weaned (excl. gilts)		0.23	0.18	0.20	0.01

WGT 1: Entry weight weaner stage (day 0 post-weaning); WGT 2: Entry weight grower stage (day 23 post-weaning); WGT 3: Entry weight finisher stage (day 48 post-weaning); WGT 5: Sample weight at 76 days post-weaning; REF: Reference category.

4.1.6 Multivariable regression analysis with autoregressive error correction

The results of the multivariable autoregressive model for 'Carcass weight' are shown in

Table 4.1.4. ‘Study week’ entered the preliminary main effect model when testing the effect of predictors not included in the full model. The model included six main effects (DF = 6) and two interaction effects (DF = 2) in addition to significant autoregressive terms at lags 1 and 2 (DF = 2). Hence, 7.9% of the available degrees of freedom were used for the model. Sixty-nine percent of the overall variance was accounted for by the structural part of the model (Regression R^2), whilst the Total R^2-value was 80.2%.

Residuals from the autoregressive model were normally distributed ($P > 0.15$) and homoscedastic with no remaining autocorrelation ($P > 0.15$). Three observations had residuals greater than 3.3 (study weeks 48, 78 and 119) with a maximum absolute value of 4.5 (Figure 4.1.21). These observations presented no obvious outliers in any predictor variables included in the model. The effect of outlier deletion had minimal effect on parameter estimates. The maximum change occurred in the AR2 term (0.41 times the standard error) after deleting observation 78. As no sensible explanation could be found for large residuals, no observation was omitted from the final model.

When fitting the selected model to the dataset with non-imputed values, all selected parameters remained significant apart from the AR1 term ($P = 0.13$). The greatest difference between parameter estimates was apparent in the AR1 term, ‘Study week’ and ‘Finisher shed’, which decreased by 0.54, 0.56 and 0.75 times the standard error, respectively. Neither the exclusion of outliers nor fitting the model to the complete dataset changed the sign of any parameter estimate.

The autocorrelation pattern of untransformed model residuals indicated that the residual series followed a second-order autoregressive process (ACF: exponential decay, PACF: drops off after lag 2) (Figure 4.1.20). Hence, the choice of an autoregressive model was justified.

Table 4.1.4. Final autoregressive model for risk factors associated with market weight of 139 batches of pigs weaned between 20 December 2000 and 20 August 2003 on farm A. Regression coefficients (‘Beta’) and their standard errors (‘SE’) are reported.

Variable	Category	Beta	SE	P-value
WEEK		0.088	0.045	0.053
WGT 1 (kg)		2.10	0.40	<0.001
WGT 3 (kg)		-3.94	1.48	0.009
Growth rate WGT 3 to WGT 5 (g/d)		0.0031	0.0015	0.049
Days to market (d)		-0.87	0.50	0.088
Finisher shed	Shed A	REF		0.015
	Shed B	0.69	0.28	
WGT 3 x Days to market		0.038	0.013	0.005
WGT 1 x WEEK		-0.012	0.005	0.018
AR1		-0.19	0.09	0.038
AR2		-0.27	0.09	0.004

WEEK: Study week; WGT 1: Entry weight weaner stage (day 0 post-weaning); WGT 3: Entry weight finisher stage (day 48 post-weaning); WGT 5: Sample weight at 76 days post-weaning; AR1: First-order autoregressive term; AR2: Second-order autoregressive term.
Intercept = 131.7, Regression R^2 = 0.691, Total R^2 = 0.802, Log-likelihood = -245.5, DF used = 11, P < 0.001.

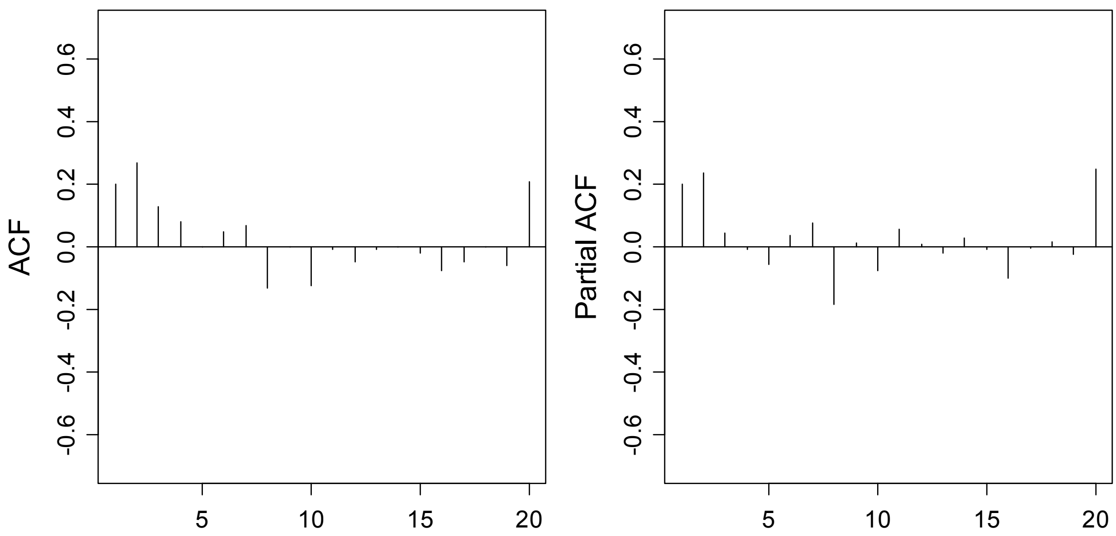

Figure 4.1.20. Autocorrelation function (ACF) and partial autocorrelation function (Partial ACF) of untransformed model residuals on pig farm A. The data set included 139 batches of pigs weaned between 20 December 2000 and 20 August 2003. The residual for one missing observation was imputed. The lag order is specified on the horizontal axis, whilst estimated autocorrelations are shown on the vertical axis.

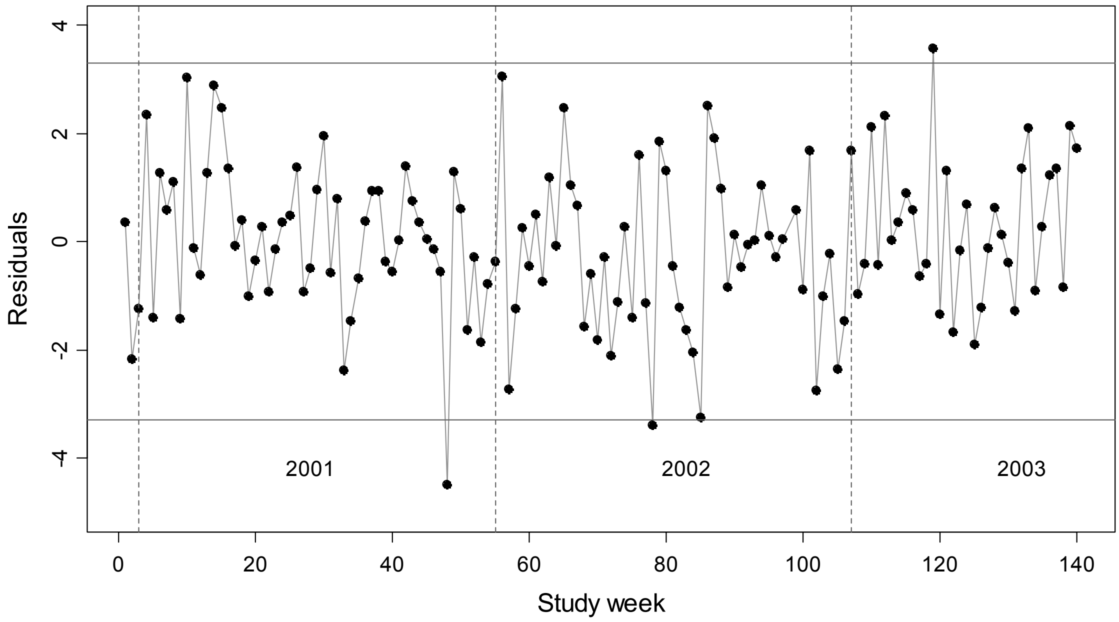

Figure 4.1.21. Time series plot of standardized residuals from the autoregressive model to predict carcass weight of batches on pig farm A. Study week identifies batches (n = 139) weaned weekly between 20 December 2000 and 20 August 2003. Horizontal lines indicate threshold values for residuals exceeding ± 3.3. Dashed vertical lines separate subsequent years.

4.1.7 Univariable ordinary least squares regression analysis

Univariable ordinary least squares analysis resulted in 17 parameters (Table 4.1.5) selected for multivariable ordinary least squares analysis. The time effects of both, 'Study week' and 'Season', were significant. 'Season', measures of weaning age (mean and variation), weight measurements and 'Days to market' showed strongest associations with 'Carcass weight' ($P < 0.001$). The effect of 'Season' indicated that batches weaned in spring were heaviest at market compared to batches weaned in other seasons. Of the other parameters, 'Weaning age', weight measurements and 'Days to market' had a positive effect on 'Carcass weight', whilst 'Coefficient of variation in weaning age' showed a negative effect.

Table 4.1.5. Predictor variables associated with market weight of 139 batches of pigs weaned between 20 December 2000 and 20 August 2003 on farm A. Continuous variables were tested for associations using univariable ordinary least squares regression analysis. Regression coefficients ('Beta') and their standard errors ('SE') as well as the coefficient of determination ('R^2') are reported.

Variable	Category	Beta	SE	P-value	R^2
WGT 3 (kg)		0.57	0.07	<0.001	0.33
WGT 1 (kg)		2.01	0.26	<0.001	0.30
WGT 2 (kg)		0.91	0.13	<0.001	0.25
Days to market (d)		0.39	0.07	<0.001	0.16
Coefficient of variation in weaning age (%)		-0.64	0.14	<0.001	0.13
Weaning age (d)		1.23	0.28	<0.001	0.12
Season of weaning	Spring: Sep to Nov	REF		<0.001	0.11
	Summer: Dec to Feb	-3.29	0.78		
	Autumn: Mar to May	-1.88	0.77		
	Winter: Jun to Aug	-2.65	0.78		
Growth rate WGT 3 to WGT 5 (g/d)		0.0106	0.0027	<0.001	0.09
Weight of pigs entering from SRL (kg)		0.63	0.18	0.001	0.08
Study week		-0.021	0.006	0.002	0.06
Percentage of piglets weaned directly (%)		-0.031	0.011	0.006	0.05
Daily feed intake weaner diet (kg/d)		-15.91	5.72	0.006	0.05
Daily feed intake finisher diet 2 (kg/d)		2.54	1.11	0.023	0.03
Median number of piglets weaned per sow		-0.82	0.46	0.076	0.02
Weaner mortality rate (%)		-0.36	0.21	0.094	0.01
Location within shed	Outer pens	REF		0.11	0.01
	Middle pens	-1.06	0.67		
Percentage of gilts farrowed (%)		-0.038	0.029	0.19	0.01

SRL: Special rearing location; WGT 1: Entry weight weaner stage (day 0 post-weaning); WGT 2: Sample weight grower stage (day 23 post-weaning); WGT 3: Entry weight finisher stage (day 48 post-weaning); WGT 5: Sample weight at 76 days post-weaning; REF: Reference category.

4.1.8 Multivariable ordinary least squares regression analysis

The results of the multivariable ordinary least squares regression model for 'Carcass weight' are shown in Table 4.1.6. The model included eleven parameters to be estimated, which presents 8.6% of the available degrees of freedom. 'Study week' interacted with 'Days to market' and 'Sample weight 1'. Furthermore, 'Sample weight 3' interacted with 'Days to market'. The model explained 81.0% of the total variance in 'Carcass weight'.

Table 4.1.6. Final ordinary least squares regression model for risk factors associated with carcass weight of 139 batches of pigs on farm A. Batches were weaned between 20 December 2000 and 20 August 2003. Regression coefficients ('Beta') and their standard errors ('SE') are reported.

Variable	Beta	SE	P-value
WEEK	-0.34	0.20	0.084
Entry numbers	0.081	0.035	0.021
WGT 1 (kg)	2.36	0.32	<0.001
WGT 3 (kg)	-4.55	1.35	0.001
Growth rate WGT 3 to WGT 5 (g/d)	0.0039	0.0015	0.009
Daily feed intake finisher diet 2 (kg/d)	2.01	0.53	<0.001
Days to market (d)	-1.37	0.48	0.005
Finisher shed	0.70	0.25	0.006
WGT 3 x Days to market	0.043	0.012	<0.001
WGT 1 x WEEK	-0.015	0.004	<0.001
Days to market x WEEK	0.0041	0.0017	0.019

WEEK: Study week; WGT 1: Entry weight weaner stage (day 0 post-weaning); WGT 3: Entry weight finisher stage (day 48 post-weaning); WGT 5: Sample weight at 76 days post-weaning.
Intercept = 166.9, Adj. $R^2 = 0.810$, $F = 49.2$, $DF = 12$, $P < 0.001$.

Residuals were normally distributed ($P > 0.15$) and showed constant variance (homoscedastic) ($P > 0.15$). Model residuals did not follow a significant trend, and neither the Durbin-Watson test statistic nor diagnostic plots revealed remaining autocorrelation in the residuals ($P > 0.15$).

Three observations had residuals greater than 3.3 (study weeks 48, 85 and 119), and the maximum absolute value was 4.3. These observations showed no outliers in any predictors. Deletion of observation 85 changed regression coefficients of five variables by more than 0.5 times the standard error (maximum change 0.65 times the standard error) without causing a change in the sign of estimates. As no sensible explanation could be found for large residuals, no observation was excluded from the analysis.

All selected parameters remained significant when fitting the selected model to the dataset with non-imputed missing values. The greatest difference between parameter estimates was apparent in 'Entry weight', 'Growth rate WGT 3 to WGT 5', 'Study week' and 'Finisher shed', which all decreased by 0.67, 0.34, 0.64 and 0.50 times the standard error, respectively, whilst no change in the sign of any parameter estimate occurred.

4.1.9 Model comparison

In comparison to the second-order autoregressive (AR2) model, the ordinary least squares (OLS) regression model included two more main effects and one additional interaction effect (Table 4.1.7). The residuals of neither of the two models were significantly autocorrelated at P-values of 0.05.

Parameters selected in the AR2 model were fitted to the OLS-model (‘reduced model’) (Table 4.1.8). The effect of including autoregressive parameters was greatest for ‘WGT 1’ and ‘Growth rate WGT 3 to WGT 5’. Compared to the AR2 model, OLS-parameter estimates for these variables were increased by 0.80 and 0.67 times the standard error.

Table 4.1.7. Comparison of regression models for predictor variables associated with carcass weight of 139 batches of pigs weaned between 20 December 2000 and 20 August 2003 on farm A. Regression parameters were derived through ordinary least squares regression analysis (OLS) or regression analysis with autoregressive error correction (AR). Regression coefficients (‘Beta’) and their standard errors (‘SE’) are reported.

Type	Variable/parameter	Beta (SE)	
		OLS	AR
Main effects			
	Intercept	166.9 (54.1)	131.7 (56.3)
	WEEK	-0.34 (0.20)	0.088 (0.045)
	Entry numbers	0.081 (0.035)	-
	WGT 1 (kg)	2.36 (0.32)	2.10 (0.40)
	WGT 3 (kg)	-4.55 (1.35)	-3.94 (1.48)
	Growth rate WGT 3 to WGT 5 (g/d)	0.0039 (0.0015)	0.0031 (0.0015)
	Daily feed intake finisher diet 2 (kg/d)	2.01 (0.53)	-
	DTM (d)	-1.37 (0.48)	-0.87 (0.50)
	Finisher shed	0.70 (0.25)	0.69 (0.28)
Interactions			
	WGT 3 x DTM	0.043 (0.012)	0.038 (0.013)
	WGT 1 x WEEK	-0.015 (0.004)	-0.012 (0.005)
	DTM x WEEK	0.0041 (0.0017)	-
Autoregressive parameters			
	AR1	-	-0.19 (0.09)
	AR2	-	-0.27 (0.09)
Model fit			
	DF used	12	9 + 2
	Lags with autocorrelation	-	-
	Regression R^2	0.810	0.691
	Total R^2	0.810	0.802

WEEK: Study week; WGT 1: Entry weight weaner stage (day 0 post-weaning); WGT 3: Entry weight finisher stage (day 48 post-weaning); WGT 5: Sample weight at 76 days post-weaning; DTM: Days to market; AR1: First-order autoregressive term; AR2: Second-order autoregressive term; DF: degrees of freedom.

Table 4.1.8. Comparison of reduced regression models for predictor variables associated with carcass weight of 139 batches of pigs weaned between 20 December 2000 and 20 August 2003 on farm A. Regression parameters were derived through ordinary least squares regression analysis (OLS) or regression analysis with autoregressive error correction (AR). Reduced model: Model parameters identified in the AR-model were fitted to the OLS-model. Regression coefficients ('Beta') and their standard errors ('SE') are reported.

Type	Variable/parameter	OLS	AR
Main effects			
	Intercept	148.9 (54.4)	131.7 (56.3)
	WEEK	0.116 (0.039)	0.088 (0.045)
	WGT 1 (kg)	2.42 (0.34)	2.10 (0.40)
	WGT 3 (kg)	-4.48 (1.45)	-3.94 (1.48)
	Growth rate WGT 3 to WGT 5 (g/d)	0.0041 (0.0016)	0.0031 (0.0015)
	DTM (d)	-1.06 (0.49)	-0.87 (0.50)
	Finisher shed	0.68 (0.27)	0.69 (0.28)
Interactions			
	WGT 3 x DTM	0.043 (0.013)	0.038 (0.013)
	WGT 1 x WEEK	-0.014 (0.004)	-0.012 (0.005)
Autoregressive parameters			
	AR1	-	-0.19 (0.09)
	AR2	-	-0.27 (0.09)
Model fit			
	DF used	9	9 + 2
	Lags with autocorrelation	1^{**}, 2^{***}, 3^{*}	-
	Regression R^2	0.776	0.691
	Total R^2	0.776	0.802

WEEK: Study week; WGT 1: Entry weight weaner stage (day 0 post-weaning); WGT 3: Entry weight finisher stage (day 48 post-weaning); WGT 5: Sample weight at 76 days post-weaning; DTM: Days to market; AR1: First-order autoregressive term; AR2: Second-order autoregressive term; DF: degrees of freedom.

Significance values: * P < 0.05, ** P < 0.01, *** P < 0.001.

4.2 Farm B

4.2.1 General

On farm B, records were available for 127 batches of pigs weaned between 26 December 2001 and 26 May 2004 (29 months). Prospective data collection commenced in study week 68. No batch was excluded from the analysis a priori.

4.2.2 Descriptive analysis

4.2.2.1 Overall

Performance differences were assessed between pens of pigs housed in sheds A to D and pens of pigs housed in shed E although all data recorded at the pen-level had been aggregated to the batch level. Eighty-nine out of all 1104 grower and 1282 finisher pens were housed in shed E. Finisher pigs in shed E were 4.8 kg heavier when entering the finisher stage, grew 62 g/d faster and took 7.8 days less to reach market weight than finisher pigs in sheds A to D (Table 4.2.1). Hence, the percentage of pigs housed in shed E was considered as a variable in the regression analysis.

Summary statistics of all relevant parameters and significance values for the effect of year, season and year x season interaction are displayed in Table 4.2.2. Breeding herd parameters were affected by year only ('Pre-weaning mortality rate' also by season), whilst 'Entry age' and 'Percentage of unaccounted pigs at the finisher stage' were influenced exclusively by season. A year x season interaction was significant for all weight measures, 'Days to market' and 'Entry numbers'. None of the batches included missing values for any of the parameters.

Table 4.2.1. Shed effect on finisher performance of pens of pigs housed in sheds A to D (n = 1193) or in shed E (n = 89). Differences in means were assessed using a t-test comparison.

Variable	Shed A to D		Shed E		P-value
	Mean	95% CI	Mean	95% CI	
Finisher start weight (kg)	64.4	64.1 - 64.7	69.2	68.0 – 70.4	<0.001
Growth rate during finisher stage (g/d)	810	805 - 815	872	839 - 906	<0.001
Days to market at finisher stage (d)	29.0	28.7 – 29.2	21.2	19.8 – 22.7	<0.001

Table 4.2.2. Descriptive statistics for performance parameters of 127 batches of pigs weaned weekly between 26 December 2001 and 26 May 2004 on farm B. Three observations were excluded for market weight and days to market due to differences in sales management. The effects of year and season were investigated as main and interaction effects (Year x Season) using Analysis of Variance (ANOVA). Effects not significant at P = 0.05 are denoted by NS.

Type	Variable	n	Mean (SD)	Median	Q1, Q3	P-value		
						Year	Season	Year x Season
Discrete variables								
	Entry numbers	127	108.1 (10.3)	107	100, 115	<0.01	<0.01	0.03
	Median number of piglets weaned per sow	127	10.3 (0.7)	10	10, 11	0.001	NS	NS
	Median parity of sows weaned (excl. gilts)	127	4.4 (1.3)	4.0	3.5, 5.0	0.005	NS	NS
Percentages								
	Pre-weaning mortality rate (%)	127	10.7 (4.4)	10.3	7.6, 12.4	<0.001	0.01	NS
	Coefficient of variation in weaning age (%)	127	8.9 (4.9)	8.2	5.4, 11.9	0.02	NS	NS
	Percentage of gilts farrowed (%)	127	19.6 (12.8)	18.2	10.0, 28.6	0.03	NS	NS
	Percentage of pigs weaned directly (%)	127	93.6 (7.3)	92.1	90.1, 100	NS	NS	NS
	Percentage of pigs in shed E (%)	127	6.6 (7.6)	7.7	0, 9.8	NS	NS	NS
	Percentage of unaccounted pigs grower stage (%)	127	1.9 (1.9)	1.4	0.8, 2.8	NS	NS	NS
	Percentage of unaccounted pigs finisher stage (%)	127	1.8 (1.6)	1.6	0.8, 2.9	NS	<0.001	NS
	Percentage of unaccounted pigs overall (%)	127	3.7 (2.4)	3.4	1.8, 5.1	NS	NS	NS
Continuous variables								
	Entry age grower stage at 43 days post-weaning (d)	127	72.8 (1.8)	72.9	71.8, 73.6	NS	0.03	NS
	Sample weight 1 at 43 days post-weaning (kg)	127	33.2 (1.7)	33.4	32.2, 34.3	0.1904	0.02	<0.01
	Sample weight 2 at 78 days post-weaning (kg)	127	64.9 (2.4)	65.0	63.7, 66.5	0.09	<0.001	<0.001
	Growth rate from sample weight 1 to 2 (g/d)	127	906 (42)	910	875, 935	0.29	<0.001	0.04
	Days to market (d)	124	106.6 (2.3)	106.9	106.0, 108.1	0.30	<0.001	<0.001
	Live weight at market (kg)	124	88.1 (2.2)	88.2	86.8, 89.9	0.21	<0.001	<0.001

Unaccounted pigs: Pigs with move-in records, but without move-out records.

4.2.2.2 Breeding herd parameters

There were two predominant features in time patterns of breeding herd parameters: First, there was a level shift in ‘Coefficient of variation in weaning age’ from a median level of 7% in 2002 to 8% in 2003 (Figure 4.2.1). This was accompanied by an increase in ‘Percentage of gilts farrowed’ from a median level of 16.7% in 2002 to 21.4% in 2003 (Figure 4.2.2). Furthermore, sows weaned excluding gilts were 0.5 to 1.0 parities younger in 2003 than in 2002 and 2004 (Figure not shown). Secondly, whilst ‘Pre-weaning mortality rate’ was 10% in 2002 and 2003, it increased to 14% in 2004 (Figure 4.2.3). Overall, the ‘Median number of pigs weaned per sow’ decreased from mid 2002 onwards as indicated by the quadratic trend line in Figure 4.2.4.

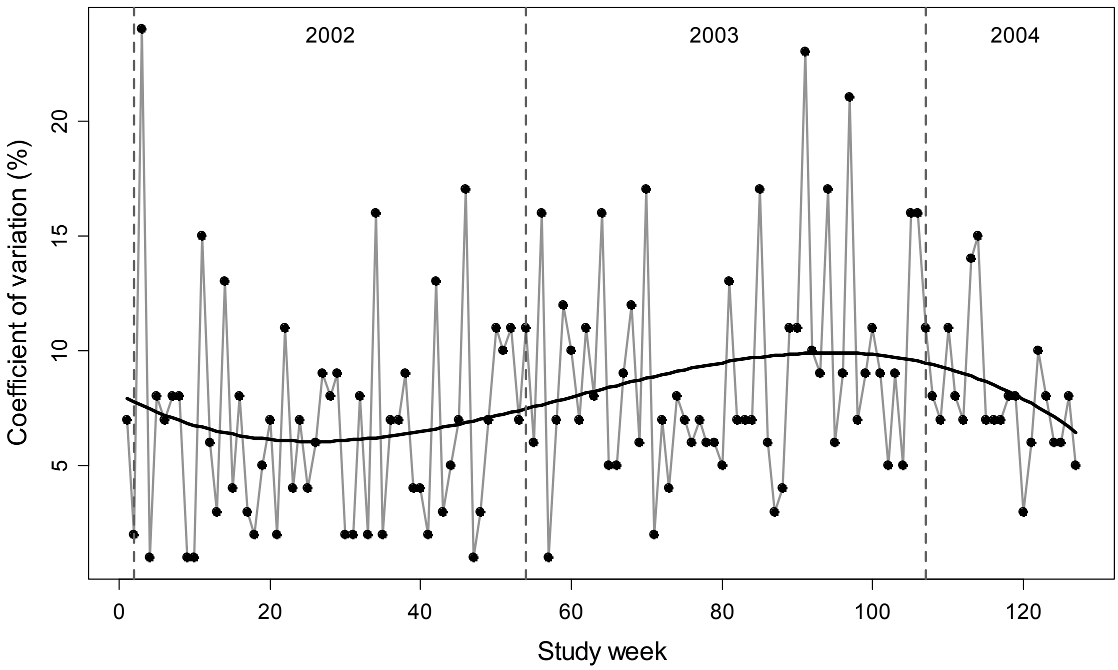

Figure 4.2.1. Time series plot of ‘Coefficient of variation in weaning age’ on pig farm B. Study week identifies batches (n = 127) weaned weekly between 26 December 2001 and 26 May 2004. Black line illustrates a fitted 3rd order polynomial trend line (F = 4.51, DF = 3, P = 0.005). Dashed lines separate subsequent years.

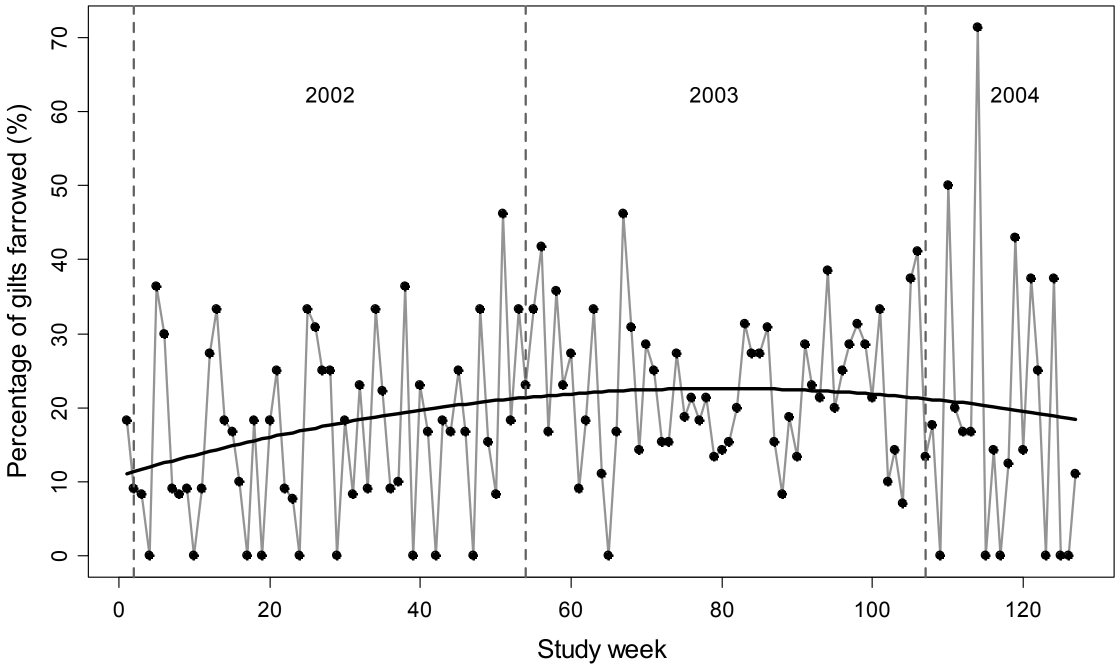

Figure 4.2.2. Time series plot of 'Percentage of gilts farrowed' on pig farm B. Study week identifies batches (n = 127) weaned weekly between 26 December 2001 and 26 May 2004. Black line illustrates a fitted quadratic trend line (F = 4.11, DF = 2, P = 0.02). Dashed lines separate subsequent years.

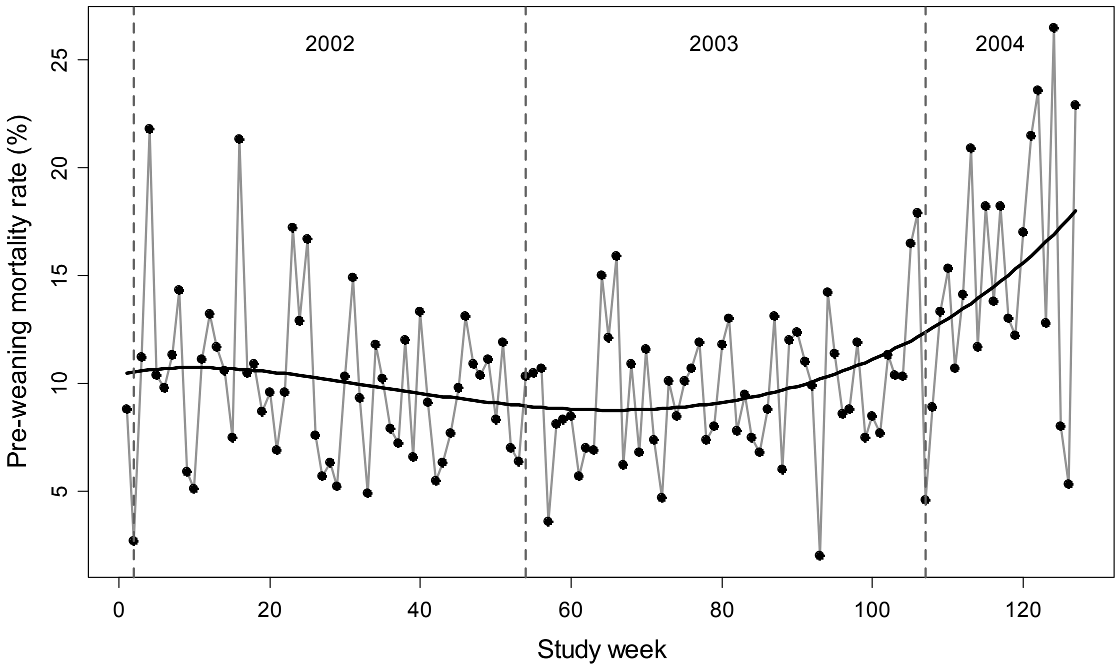

Figure 4.2.3. Time series plot of 'Pre-weaning mortality rate' on pig farm B. Study week identifies batches (n = 127) weaned weekly between 26 December 2001 and 26 May 2004. Black line illustrates a fitted 3rd order polynomial trend line (F = 12.97, DF = 3, P < 0.001). Dashed lines separate subsequent years.

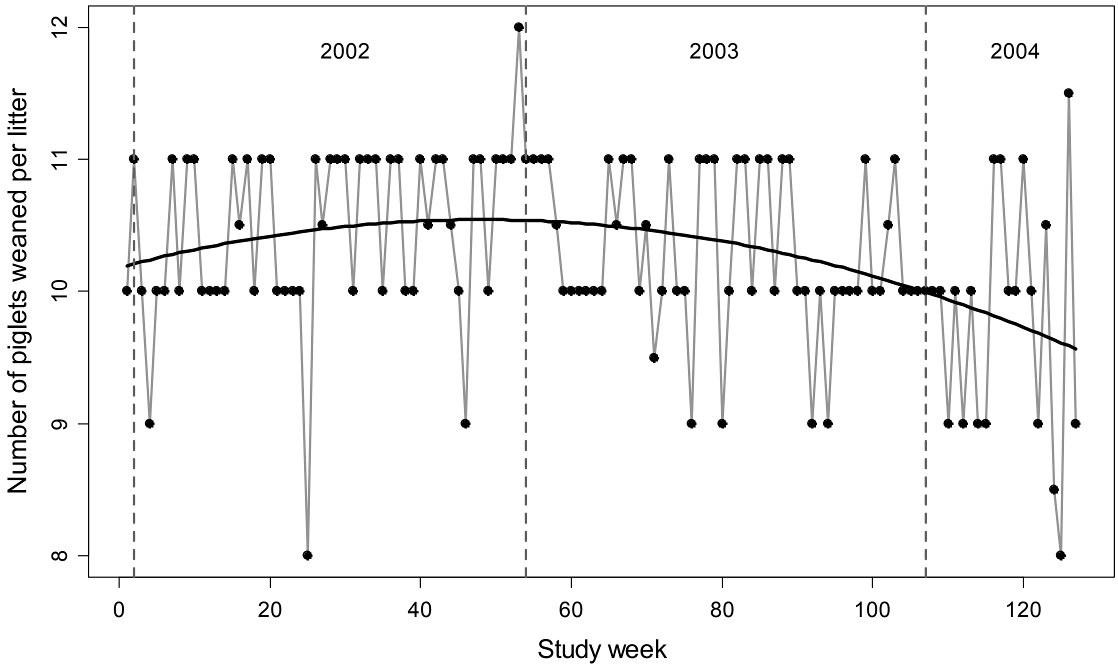

Figure 4.2.4. Time series plot of 'Number of pigs weaned per sow' on pig farm B. Study week identifies batches (n = 127) weaned weekly between 26 December 2001 and 26 May 2004. Black line illustrates a fitted quadratic trend line ($F = 9.47$, $DF = 2$, $P < 0.001$). Dashed lines separate subsequent years.

4.2.2.3 Entry parameters

The median number of pigs entering a batch at the grower stage was 107 (Figure 4.2.5). Whilst the median level of 'Entry numbers' was similar in 2002 (median: 112) and 2004 (median: 110), 'Entry numbers' declined throughout 2003 (median: 102).

The age of pigs entering the grower stage (Figure not shown) was highly consistent up to study week 97 (mean: 72.8 d, SD: 1.0 d). Thereafter, 'Entry age' showed considerably greater variation (mean: 72.5 d, SD: 3.2 d) with extremes of entry age in study weeks 101 (66.1 d) and 111 (79.6 d). 'Percentage of finisher pigs housed in shed E' did not follow a trend. Out of 65 batches, 9.9% of the pigs (Range: 7.6 to 31.0%) were housed in shed E.

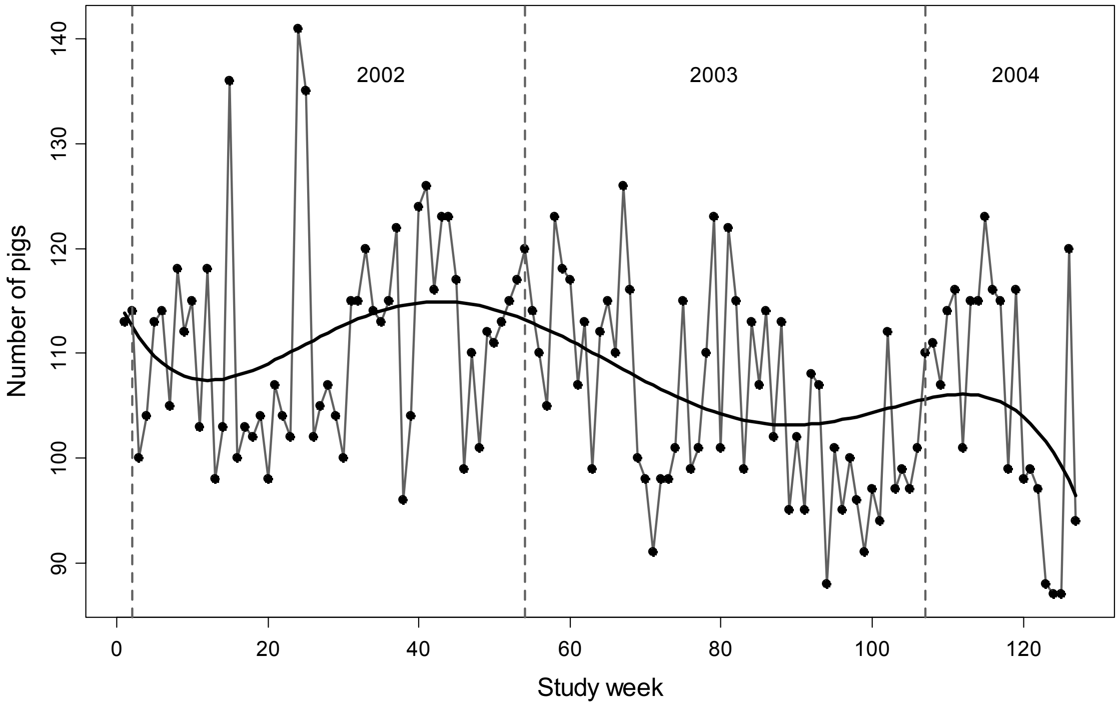

Figure 4.2.5. Time series plot of number of pigs entering the grower stage on pig farm B. Study week identifies batches (n = 127) weaned weekly between 26 December 2001 and 26 May 2004. Black line illustrates a fitted 5th order polynomial trend line ($F = 5.06$, $DF = 5$, $P < 0.001$). Dashed lines separate subsequent years.

4.2.2.4 Deaths and sick pig movements

Neither death records nor records of sick pig movements were submitted to analysis due to inconsistent and incomplete data. This implies that any pig that died or that was moved to a hospital pen will appear as an unaccounted pig.

4.2.2.5 Unaccounted pigs

Lower pig counts than at the previous production stage (positive value of 'Unaccounted pig') occurred in 77.2% and 75.6% of the batches at the grower and finisher stage, respectively. Out of these batches, the median number of unaccounted pigs was 2 (Range: 1 to 13) at the grower stage and 2 (Range: 1 to 8) at the finisher stage. At neither production stage, 'Percentage of unaccounted pigs' changed significantly over time. In two grower and nine finisher batches, more pigs were sold than recorded as entered (Range: -1 to -4).

4.2.2.6 Sample weights

Farm B weighed the entire batch at each weight measurement. The mean weight of pigs was 33.2 kg and 64.9 kg at 43 and 78 days post-weaning, respectively. The grower/finisher growth rate from 43 days post-weaning to market was 863 g/d.

Figure 4.2.6 illustrates the batch-specific growth curves from entry to the grower shed (43 days post-weaning) to market weight stratified by 6-month periods. The graphs indicate very low variation in sample weight measurements within and between strata.

A fourth order polynomial trend line best described time patterns of sample weight 1 (Figure 4.2.7) and sample weight 2 (Figure not shown). Both sample weights declined in the first half of 2002 and increased slightly in the second half. During 2003, measurements of both sample weights declined until reaching a trough at the end of 2003 and increased thereafter. 'Growth rate WGT 1 to WGT 2' showed a similar time pattern (Figure 4.2.8).

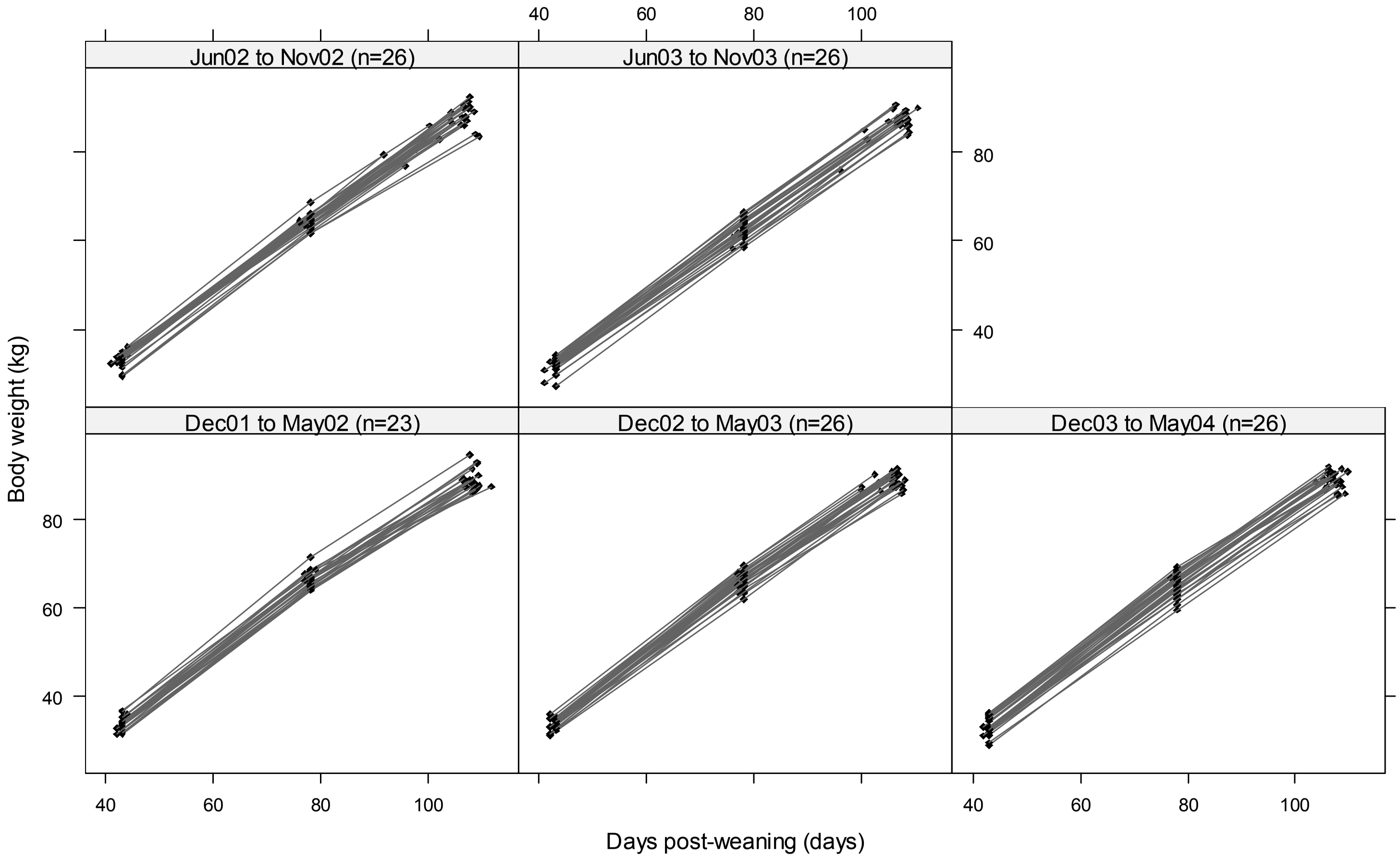

Figure 4.2.6. Batch-specific growth curves from entry to the grower stage (day 43 post-weaning) until market for 127 batches weaned between 26 December 2001 and 26 May 2004 on pig farm B. Growth curves were stratified by six-month periods.

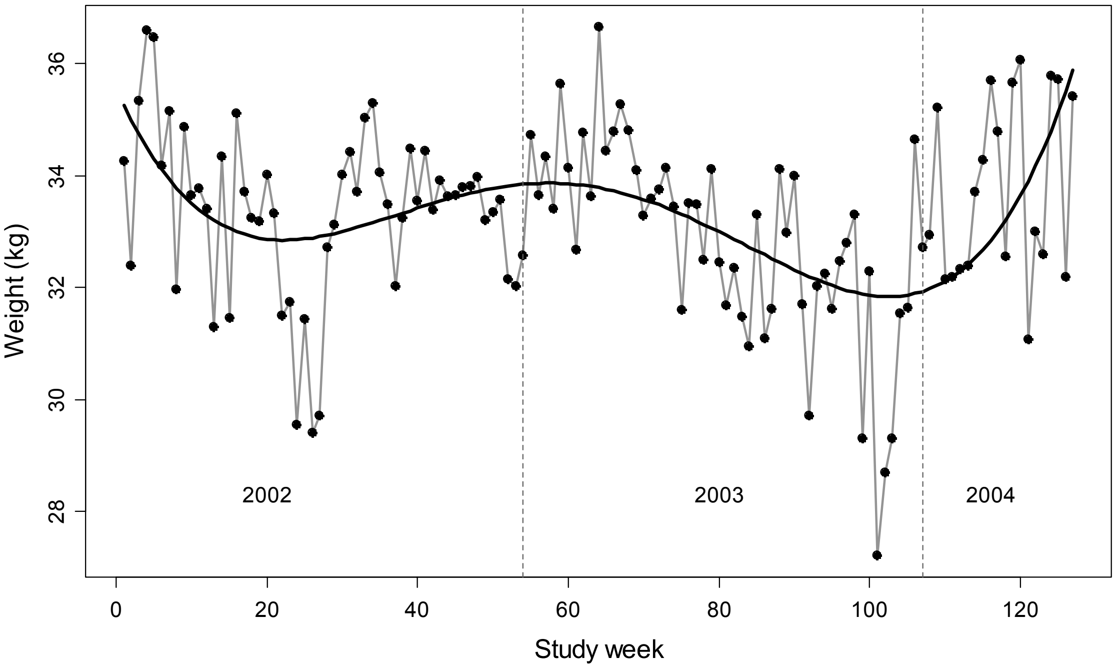

Figure 4.2.7. Time series plot of 'Sample weight 1' (day 43 post-weaning) on pig farm B. Study week identifies batches (n = 127) weaned weekly between 26 December 2001 and 26 May 2004. Black line illustrates a fitted 4th order polynomial trend line (F = 9.60, DF = 4, P < 0.001). Dashed lines separate subsequent years.

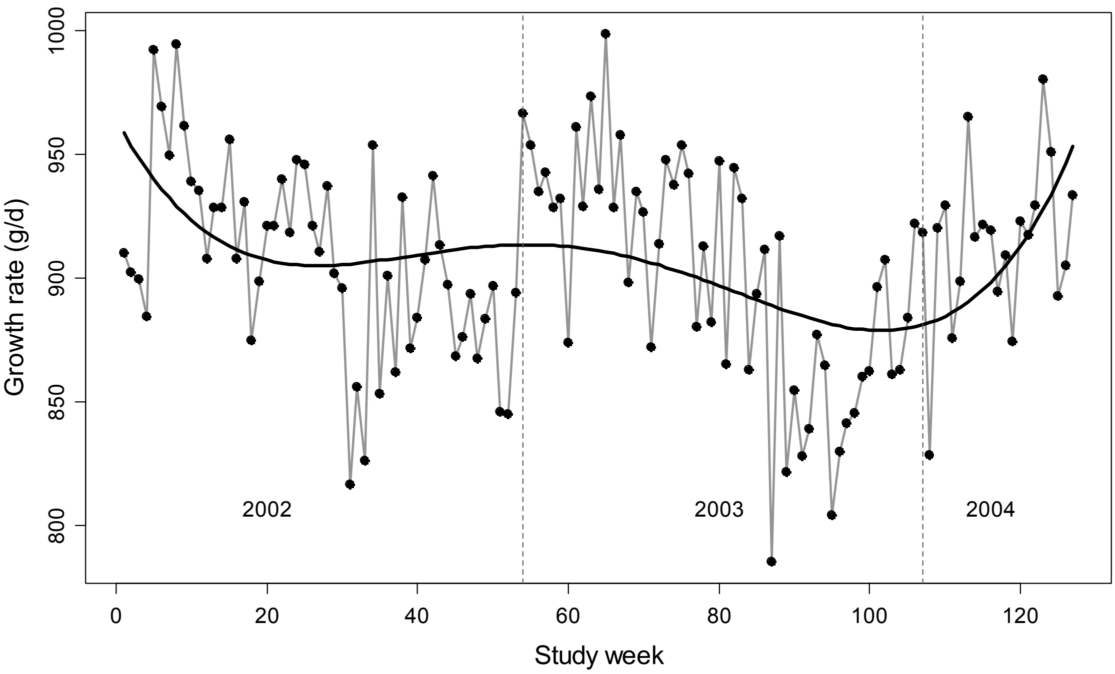

Figure 4.2.8. Time series plot of growth rate from sample weight 1 (day 43 post-weaning) to sample weight 2 (day 78 post-weaning) on pig farm B. Study week identifies batches (n = 127) weaned weekly between 26 December 2001 and 26 May 2004. Black line illustrates a fitted 4th order polynomial trend line (F = 6.25, DF = 4, P < 0.001). Dashed lines separate subsequent years.

4.2.2.7 Market parameters

Throughout the study period, ‘Market weight’ was relatively stable apart from two clusters of low market weights between study weeks 35 and 38 as well as between study weeks 88 and 90 (Figure 4.2.9). Low market weights of these batches were related to sale events during the pre-Christmas period. As different marketing patterns during the pre-Christmas period have no biological meaning, it was decided to exclude three observations with market weights less than 80 kg (study weeks 37, 38 and 89). The two clusters of low ‘Days to market’ (Figure 4.2.10) between study weeks 33 and 38 and between study weeks 88 and 90 corresponded with the two clusters of low pre-Christmas market weights. Pigs of the remaining batches (n = 124) were marketed after a mean time of 106.6 days post-weaning at a mean live weight of 88.1 kg. Hence, mean daily growth rate from birth to market live weight was 634 g/d (estimated entry age: 29.9 days). In contrast to ‘Market weight’, which tended to decrease in the first half of 2003, ‘Days to market’ increased over the same period.

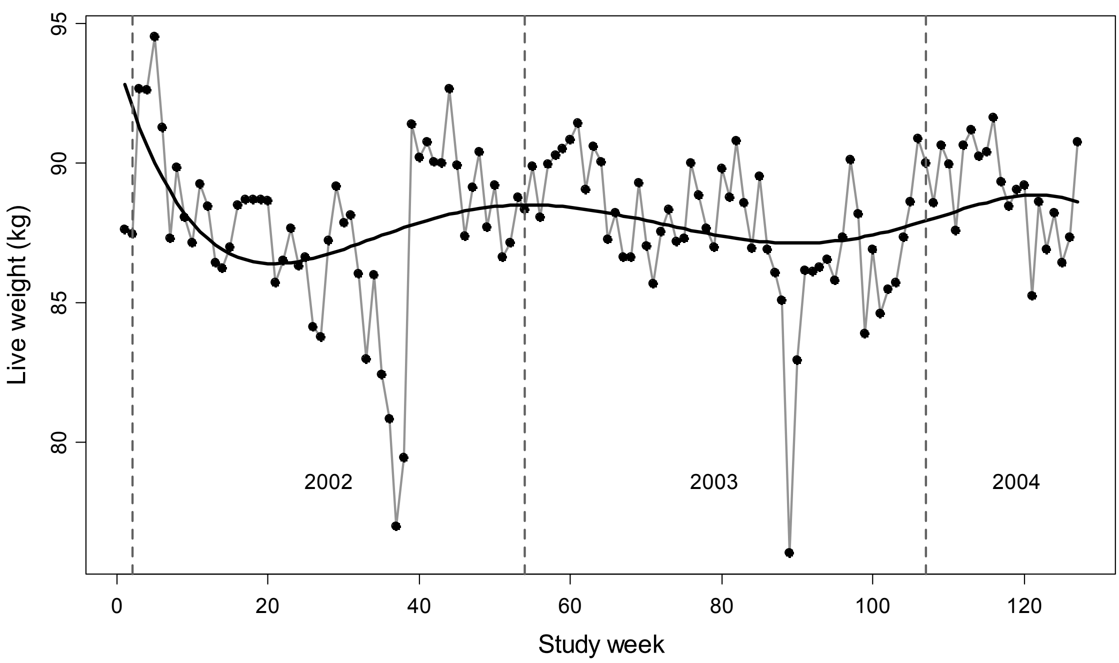

Figure 4.2.9. Time series plot of ‘Market weight’ on pig farm B. Study week identifies batches (n = 127) weaned weekly between 26 December 2001 and 26 May 2004. Black line illustrates a fitted 5th order polynomial trend line (F = 3.75, DF = 5, P = 0.003). Dashed lines separate subsequent years.

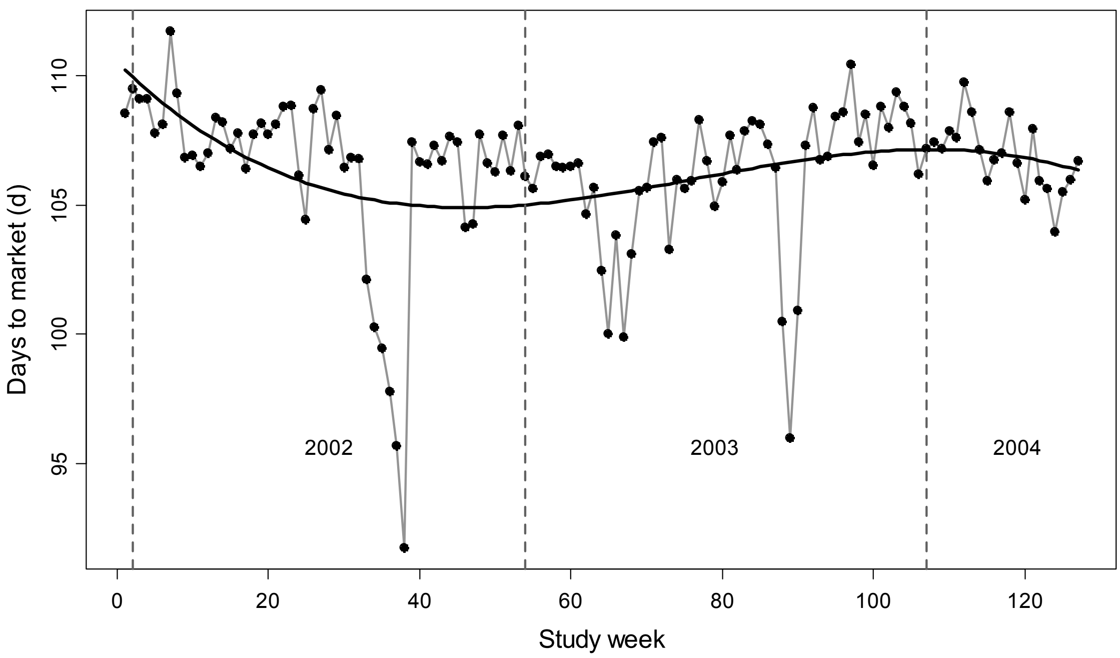

Figure 4.2.10. Time series plot of 'Days to market' on pig farm B. Study week identifies batches (n = 127) weaned weekly between 26 December 2001 and 26 May 2004. Black line indicates 3rd order polynomial trend line (F = 7.58, DF = 3, P < 0.001). Dashed lines separate subsequent years.

4.2.2.8 Feed parameters

Feed intake data were not recorded on farm B.

4.2.3 Univariable time series analysis

Inspection of the autocorrelation function (ACF) and the partial autocorrelation function (PACF) indicated that 'Market weight' followed a first-order autoregressive process with positive autocorrelation (Figure 4.2.11), since the ACF decayed exponentially and the PACF dropped off after lag 1.

As suspected from the ACF and PACF, backward elimination of autoregressive terms resulted in a first-order autoregressive term of -0.61 (SE ± 0.07). This model enabled to forecast the immediate future value with 36.2% accuracy as indicated by the total R-square. Residuals of this univariable autoregressive model showed remaining positive autocorrelation at lags 3 (P = 0.005) and 14 (P = 0.04).

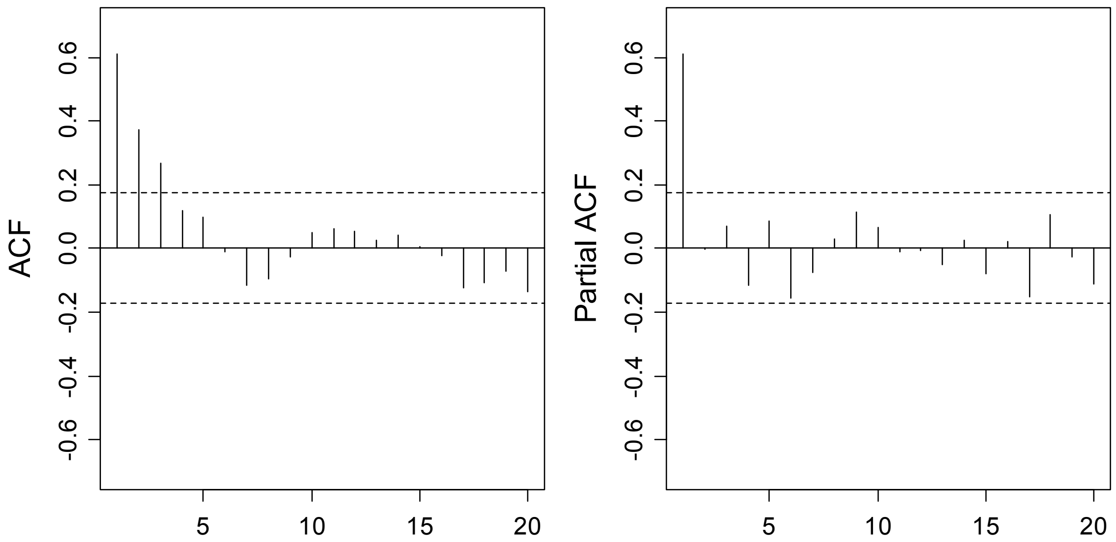

Figure 4.2.11. Autocorrelation function (ACF) and partial autocorrelation function (Partial ACF) of market weight of 127 batches of pigs weaned between 26 December 2001 and 26 May 2004 on farm B. Three excluded observations were imputed. Dashed lines indicate 5% significance level that autocorrelation is zero. The lag order is specified on the horizontal axis, whilst estimated autocorrelations are shown on the vertical axis.

4.2.4 Collinearity between predictor variables

'Sample weight 1' was highly correlated with 'Sample weight 2' ($r = 0.810$), whereas it showed low correlation with 'Growth rate WGT 1 to WGT 2' ($r = 0.186$). Hence, 'Growth rate WGT 1 to WGT 2' was chosen in preference to 'Sample weight 2'.

4.2.5 Univariable regression analysis with autoregressive error correction

Univariable analysis (Table 4.2.3) resulted in eight parameters selected for multivariable analysis. Batches with high market weights were significantly heavier when entering the grower stage ($P < 0.001$) and exhibited significantly greater growth rates during the grower stage ($P = 0.002$). Furthermore, time to marketing had a positive effect on 'Market weight' ($P = 0.06$). Neither season nor year resulted in P-values less than 0.20 when accounting for positive autocorrelation at lag 1. It is interesting to note that 'Pre-weaning mortality rate' and 'Coefficient of variation in weaning age' showed a positive association with 'Market weight'.

Table 4.2.3. Variables associated with market weight of 124 batches of pigs weaned between 26 December 2001 and 26 May 2004 on farm B. Variables were tested for associations using a first-order autoregressive model. The first-order autoregressive term was highly significant ($P < 0.001$) for all variables. Regression coefficients ('Beta') and their standard errors ('SE') are reported. The Regression R^2 (Regr. R^2) indicates the accuracy of the structural part of the model after autoregressive transformation.

Variable	Beta	SE	P-value	Regr. R^2
WGT 1 (kg)	0.46	0.10	<0.001	0.15
Growth rate WGT 1 to WGT 2 (g/d)	0.013	0.004	0.002	0.08
Pre-weaning mortality rate (%)	0.083	0.034	0.02	0.05
Days to market (d)	0.17	0.09	0.06	0.03
Median number of piglets weaned per sow	-0.35	0.20	0.08	0.03
Coefficient of variation in weaning age (%)	0.048	0.028	0.10	0.02
Median parity of sows weaned (excl. gilts)	0.18	0.11	0.12	0.02
Percentage of unaccounted pigs at the finisher stage (%)	-0.12	0.08	0.14	0.02

WGT 1: Entry weight grower stage (43 days post-weaning); WGT 2: Entry weight finisher stage (78 days post-weaning).

4.2.6 Multivariable regression analysis with autoregressive error correction

After the collinearity study and the univariable analysis, eight variables with P-values < 0.20 were offered to the multivariable model. The stepwise model selection procedure resulted in a model including a first-order autoregressive term (DF = 1) in addition to five main effects (DF = 8) and two interaction effects (DF = 6) (Table 4.2.4). Sixty-one percent of the overall variance was accounted for by the structural part of the model (Regression R^2), whilst the total R^2-value based on both, the structural and the autoregressive part of the model, was 73.3%.

Untransformed residuals followed a first-order autoregressive process, since the Autocorrelation Function decayed slowly and the Partial Autocorrelation Function dropped off after lag 1 (Figure 4.2.12). Hence, the choice of an autoregressive model was justified. Residuals from the autoregressive model were normally distributed ($P = 0.08$) with values ranging between -3.5 and +2.6 (Figure 4.2.13). Only in study week 7, residuals exceeded three standard deviations, and no explanation could be found for its presence. Exclusion of this outlier had minimal effects on parameter estimates. The LM-test indicated heteroscedastic residuals at lags 10 ($P = 0.04$) and 11 ($P = 0.05$), whilst the Q-test did not identify heteroscedasticity up to lag 12 given a P-value of 0.05. The residual series did not reveal any remaining autocorrelation ($P > 0.15$).

Table 4.2.4. Final autoregressive model for risk factors associated with market weight of 124 batches of pigs weaned between 26 December 2001 and 26 May 2004 on farm B. Regression coefficients ('Beta') and their standard errors ('SE') are reported.

Variable	Category	Beta	SE	P-value
WGT 1 (kg)		1.20	0.18	<0.001
Growth rate WGT 1 to WGT 2 (g/d)		0.023	0.003	<0.001
DTM (d)		0.96	0.16	<0.001
Season	Spring: Sep to Nov	REF		0.001
	Summer: Dec to Feb	-0.84	0.56	
	Autumn: Mar to May	-1.91	0.57	
	Winter: Jun to Aug	-0.87	0.66	
Finisher shed type	Type A	REF		0.002
	Type B	1.04	0.33	
	Type C	0.66	0.29	
Season x DTM	Spring x DTM	REF		<0.001
	Summer x DTM	-0.91	0.24	
	Autumn x DTM	-0.56	0.20	
	Winter x DTM	-0.19	0.20	
Season x WGT 1	Spring x WGT 1	REF		<0.001
	Summer x WGT 1	-0.78	0.21	
	Autumn x WGT 1	-0.50	0.23	
	Winter x WGT 1	-0.12	0.28	
AR1		-0.41	0.09	<0.001

WGT 1: Entry weight grower stage (day 43 post-weaning); WGT 2: Entry weight finisher stage (day 78 post-weaning); DTM: Days to market; DTM and WGT1 were centred by subtracting their median; AR1: First-order autoregressive term.

Intercept = 68.6, Regression R^2 = 0.609, Total R^2 = 0.733, Log-likelihood = -194.0, DF = 16, P < 0.001.

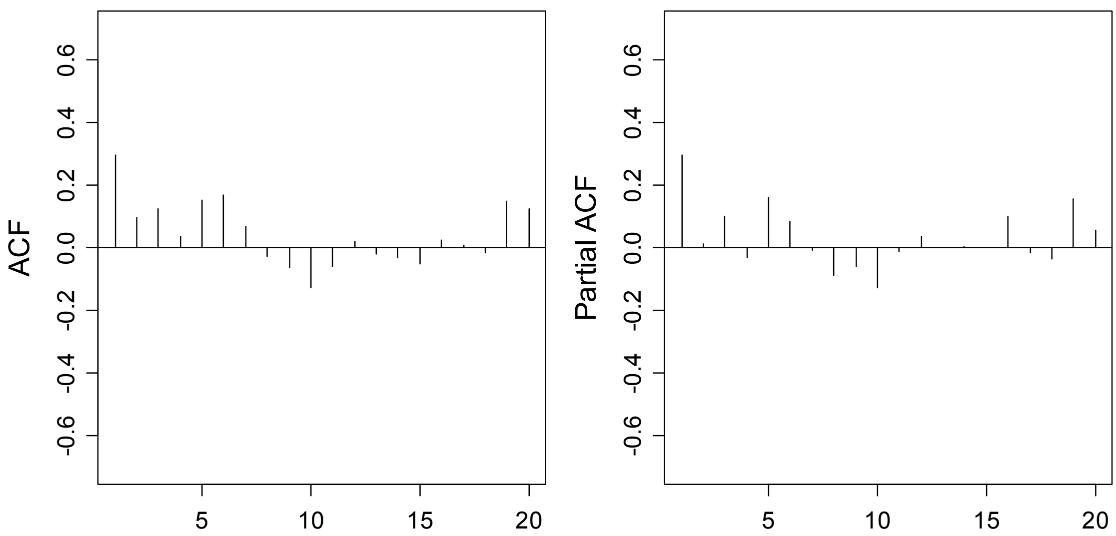

Figure 4.2.12. Autocorrelation function (ACF) and partial autocorrelation function (Partial ACF) of untransformed model residuals on pig farm B. The data set included 127 batches of pigs weaned between 26 December 2001 and 26 May 2004. Three excluded observations were imputed. The lag order is specified on the horizontal axis, whilst estimated autocorrelations are shown on the vertical axis.

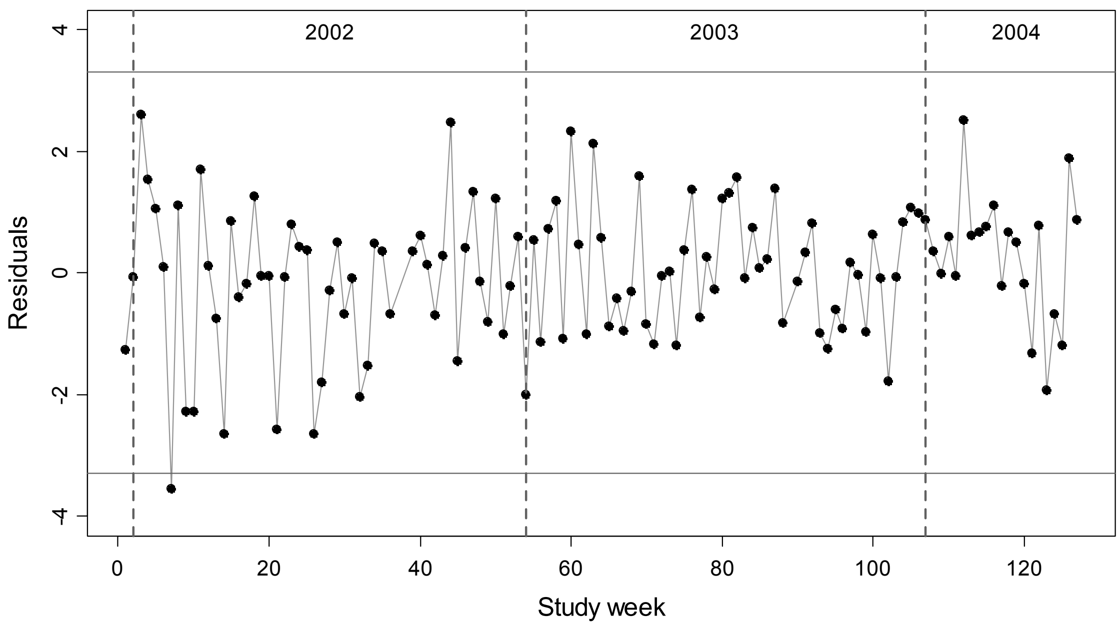

Figure 4.2.13. Time series plot of standardized residuals from the autoregressive model to predict market weight of batches of pigs on farm B. Study week identifies batches (n = 124) weaned weekly between 26 December 2001 and 26 May 2004. Horizontal lines indicate threshold values for standardized residuals exceeding ± 3.3. Dashed vertical lines separate subsequent years.

4.2.7 Univariable ordinary least squares regression analysis

After univariable screening (Table 4.2.5) eight variables with P-values < 0.20 were offered to the multivariable model. Regression coefficients for 'Season' indicated that batches of pigs weaned in summer were heaviest, whilst batches weaned in winter were lightest at market. 'Median number of piglets weaned per sow' was negatively associated with 'Market weight', whilst all other continuous variables showed positive associations with market weight. According to univariable analysis, an increase in 'Pre-weaning mortality rate' was associated with greater market weight.

Table 4.2.5. Predictor variables associated with market weight of 124 batches of pigs weaned between 26 December 2001 and 26 May 2004 on farm B. Variables were tested for associations using univariable ordinary least squares regression analysis. Regression coefficients ('Beta') and their standard errors ('SE') as well as the coefficient of determination ('R^2') are reported.

Variable	Category	Beta	SE	P-value	R^2
WGT 1 (kg)		0.58	0.11	<0.001	0.19
Growth rate WGT 1 to WGT 2 (g/d)		0.017	0.005	<0.001	0.09
Days to market (d)		0.31	0.08	<0.001	0.09
Season of weaning	Spring: Sep to Nov	REF		0.02	0.13
	Summer: Dec to Feb	1.30	0.56		
	Autumn: Mar to May	0.03	0.55		
	Winter: Jun to Aug	-1.19	0.60		
Pre-weaning mortality rate (%)		0.094	0.045	0.04	0.03
Age when entering the grower stage (d)		0.16	0.11	0.16	0.01
Median number of piglets weaned per sow		-0.38	0.27	0.17	0.01
Entry numbers grower stage		0.025	0.020	0.20	0.01

WGT 1: Entry weight grower stage (day 43 post-weaning); WGT 2: Entry weight finisher stage (day 78 post-weaning).

4.2.8 Multivariable ordinary least squares regression analysis

Table 4.2.6 describes the results from the multivariable ordinary least squares (OLS) regression model to determine risk factors for 'Market weight' on farm B. Seven main effects (DF = 10) and two interaction effects (DF = 6) were found significant after the stepwise procedure. There was a strong effect of 'Entry weight grower stage' (WGT 1), 'Growth rate during the grower stage', 'Days to market' (DTM) and 'Season' on final market weight of batches ($P < 0.001$). Furthermore, the shed type during the finisher stage had a significant effect on 'Market weight'. A Season x DTM interaction was detected such that the effect of 'Days to market' on 'Market weight' was decreased by 0.84, 0.50 and 0.07 kg for batches weaned in summer, autumn and winter, respectively, compared to batches weaned in spring. Similarly, the significant Season x WGT 1 interaction indicates that the effect of WGT 1 was greatest in batches weaned in spring followed by batches weaned in winter, autumn and summer. The model explained 67.4% of the variance in 'Market weight'.

Residuals were approximately normally distributed ($P = 0.06$) and ranged from -3.2 to +2.6, indicating no outliers with residuals greater than 3.3.

Inspection of the diagnostic plots of the residuals against the predicted values indicated homoscedasticity. Homoscedasticity of residuals was confirmed since neither the Q- nor the LM-test were significant ($P > 0.15$). Residual positive autocorrelation was present at lag 1 ($P < 0.001$) and lag 6 ($P = 0.02$) as assessed by the Durbin-Watson statistics.

Table 4.2.6. Final ordinary least squares regression model for risk factors associated with market weight of 124 batches of pigs on farm B. Batches were weaned between 26 December 2001 and 26 May 2004. Regression coefficients ('Beta') and their standard errors ('SE') are reported.

Variable	Category	Beta	SE	P-value
WGT 1 (kg)		1.25	0.18	<0.001
Growth rate WGT 1 to WGT 2 (g/d)		0.021	0.004	<0.001
DTM (d)		0.91	0.16	<0.001
Number of pigs weaned per sow		-0.48	0.17	<0.01
Number of pigs entering the grower stage		0.03	0.01	0.049
Season	Spring: Sep to Nov	REF		<0.001
	Summer: Dec to Feb	-0.63	0.42	
	Autumn: Mar to May	-1.98	0.41	
	Winter: Jun to Aug	-0.80	0.46	
Finisher shed type	Shed A or B	REF		0.02
	Shed C	0.02	0.00	
	Shed D	0.91	0.16	
Season x DTM	Spring x DTM	REF		<0.001
	Summer x DTM	-0.84	0.23	
	Autumn x DTM	-0.50	0.20	
	Winter x DTM	-0.07	0.19	
Season x WGT 1	Spring x WGT	REF		<0.01
	Summer x WGT	-0.72	0.22	
	Autumn x WGT	-0.45	0.25	
	Winter x WGT	-0.13	0.27	

WGT 1: Entry weight grower stage (day 43 post-weaning), re-scaled by subtracting median; WGT 2: Entry weight finisher stage (day 78 post-weaning); DTM: Days to market, re-scaled by subtracting median; DTM and WGT1 were centred by subtracting their median.
Intercept = 72.4, Adj. R^2 = 0.674, F = 16.9, DF = 17, P < 0.001.

4.2.9 Model comparison

In comparison to the autoregressive (AR) model, the ordinary least squares (OLS) regression model included two more main effects (Table 4.2.7). Residual autocorrelation was present in the OLS regression model, but not in the AR-model.

The OLS regression model and the AR-model accounted for 67% and 61% of the overall variance in 'Market weight', respectively. Whilst this 6% higher accuracy applies to the structural part of the model, the structural and autoregressive part of the model predicted observations with an accuracy of 73%. An OLS regression model including the same parameters as identified in the AR-model ('reduced regression model') showed remaining autocorrelation at lags 1, 5, 6 and 7 (Table 4.2.8).

Table 4.2.7. Comparison of regression models for predictor variables associated with market weight of 124 batches of pigs weaned between 26 December 2001 and 26 May 2004 on farm B. Regression parameters were derived through ordinary least squares regression analysis (OLS) or regression analysis with autoregressive error correction (AR). Regression coefficients ('Beta') and their standard errors ('SE') are reported.

Type	Variable/parameter	Category	Beta (SE)	
			OLS	AR
Main effects				
	Intercept		72.4 (3.6)	68.6 (3.0)
	WGT 1 (kg)		1.25 (0.18)	1.20 (0.18)
	Growth rate WGT 1 to WGT 2 (g/d)		0.021 (0.004)	0.023 (0.003)
	DTM (d)		0.91 (0.16)	0.96 (0.16)
	Number of pigs weaned per sow		-0.48 (0.17)	-
	Number of pigs entering the grower stage		0.027 (0.013)	-
	Season	Spring: Sep to Nov	REF	REF
		Summer: Dec to Feb	-0.63 (0.42)	-0.84 (0.56)
		Autumn: Mar to May	-1.98 (0.41)	-1.91 (0.57)
		Winter: Jun to Aug	-0.80 (0.46)	-0.87 (0.66)
	Finisher shed type	Type 1	REF	REF
		Type 2	0.87 (0.37)	1.04 (0.33)
		Type 3	0.59 (0.27)	0.66 (0.29)
Interactions				
	Season x DTM	Spring x DTM	REF	REF
		Summer x DTM	-0.84 (0.23)	-0.91 (0.24)
		Autumn x DTM	-0.49 (0.2)	-0.56 (0.2)
		Winter x DTM	-0.07 (0.19)	-0.19 (0.2)
	Season x WGT 1	Spring x WGT	REF	REF
		Summer x WGT	-0.72 (0.22)	-0.78 (0.21)
		Autumn x WGT	-0.45 (0.25)	-0.50 (0.23)
		Winter x WGT	-0.13 (0.27)	-0.12 (0.28)
Autoregressive parameters				
	AR1		-	-0.41 (0.09)
Model fit				
	DF used		17	15 + 1
	Significant autocorrelations		Lags 1***, 3*, 5*, 6*	-
	Regression R^2		0.674	0.609
	Total R^2		0.674	0.733

REF: Reference category; WGT 1: Entry weight grower stage (day 43 post-weaning), (re-scaled by subtracting median); WGT 2: Entry weight finisher stage (day 78 post-weaning); DTM: Days to market, re-scaled by subtracting median; AR1: First-order autoregressive term; DF: degrees of freedom.
Significance values: * $P < 0.05$, ** $P < 0.01$, *** $P < 0.001$.

Table 4.2.8. Comparison of reduced regression models for predictor variables associated with market weight of 124 batches of pigs weaned between 26 December 2001 and 26 May 2004 on farm B. Regression parameters were derived through ordinary least squares regression analysis (OLS) or regression analysis with autoregressive error correction (AR). Reduced model: Model parameters identified in the AR-model were fitted to the OLS-model. Regression coefficients ('Beta') and their standard errors ('SE') are reported.

Type	Variable/parameter	Category	Beta (SE)	
			OLS	AR
Main effects				
	Intercept		69.9 (3.2)	68.6 (3.0)
	WGT 1 (kg)		1.30 (0.18)	1.20 (0.18)
	Growth rate WGT 1 to WGT 2 (g/d)		0.021 (0.004)	0.023 (0.003)
	DTM (d)		0.91 (0.17)	0.96 (0.16)
	Season	Spring: Sep to Nov	REF	REF
		Summer: Dec to Feb	-0.62 (0.43)	-0.84 (0.56)
		Autumn: Mar to May	-2.08 (0.42)	-1.91 (0.57)
		Winter: Jun to Aug	-1.02 (0.47)	-0.87 (0.66)
	Finisher shed type	Type 1	REF	REF
		Type 2	1.06 (0.37)	1.04 (0.33)
		Type 3	0.68 (0.28)	0.66 (0.29)
Interactions				
	Season x DTM	Spring x DTM	REF	REF
		Summer x DTM	-0.85 (0.23)	-0.91 (0.24)
		Autumn x DTM	-0.48 (0.20)	-0.56 (0.2)
		Winter x DTM	-0.14 (0.20)	-0.19 (0.2)
	Season x WGT 1	Spring x WGT	REF	REF
		Summer x WGT	-0.73 (0.22)	-0.78 (0.21)
		Autumn x WGT	-0.47 (0.25)	-0.50 (0.23)
		Winter x WGT	-0.31 (0.27)	-0.12 (0.28)
Autoregressive parameters				
	AR1		-	-0.41 (0.09)
Model fit				
	DF used		15	15 + 1
	Significant autocorrelations		Lags 1***, 3*, 5*, 6*, 7*	-
	Regression R^2		0.650	0.609
	Total R^2		0.650	0.733

REF: Reference category; WGT 1: Entry weight grower stage (day 43 post-weaning), (re-scaled by subtracting median); WGT 2: Entry weight finisher stage (day 78 post-weaning); DTM: Days to market, re-scaled by subtracting median; AR1: First-order autoregressive term; DF: degrees of freedom.
Significance values: * P < 0.05, ** P < 0.01, *** P < 0.001.

4.3 Farm C

4.3.1 General

The study period on farm C involved 90 study weeks between 5 June 2003 and 17 February 2005 (21 months). Throughout this study period, no batch of pigs was weaned in study weeks 10 and 69 ('missing observation'). Weaning of two batches within one week occurred in study weeks 38 and 88. On these occasions, the additional batch was reared and marketed differently from the other batches, thus being excluded from the analysis. As a result, the final data set consisted of 88 batches weaned throughout 90 study weeks.

4.3.2 Descriptive analysis

4.3.2.1 Overall

Summary statistics of all relevant parameters and significance values for the effect of year and season are displayed in Table 4.3.1. A significant year effect as seen in 'WGT 1' was also apparent in 'Days to market'. A seasonal effect was detected for 'Entry numbers' and market parameters.

Table 4.3.1. Descriptive statistics for performance parameters of 88 batches of pigs weaned weekly between 5 June 2003 and 17 February 2005 on farm C. The effects of year and season were investigated as main and interaction effects (Year x Season) using Analysis of Variance (ANOVA). Effects not significant at P = 0.05 are denoted by NS.

Variable type	Variable	n	Mean (SD)	Median	Q1, Q3	Missing	P-value		
							Year	Season	Season x Year
Discrete variables									
	Entry numbers	88	76.8 (7.6)	77.5	72.0, 82.0	0	NS	0.017	NS
Percentages									
	Percentage of gilts farrowed (%)	88	18.8 (16.7)	15.8	0.0, 26.4	0	NS	NS	NS
	Weaner mortality rate (%)	88	0.9 (1.3)	0.0	0.0, 1.4	0	NS	NS	NS
	Grower mortality rate (%)	88	0.4 (0.8)	0.0	0.0, 0.0	0	NS	NS	NS
	Finisher mortality rate (%)	88	0.2 (0.5)	0.0	0.0, 0.0	0	NS	NS	NS
	Overall mortality rate (%)	88	1.5 (1.5)	1.3	0.0, 2.3	0	NS	NS	NS
	Percentage of unaccounted pigs at weaner stage (%)	88	0.7 (1.5)	0.0	0.0, 0.6	0	NS	NS	NS
	Percentage of unaccounted pigs at grower stage (%)	88	0.2 (1.2)	0.0	0.0, 0.0	0	NS	NS	NS
	Percentage of unaccounted pigs at finisher stage (%)	88	0.4 (1.9)	0.0	0.0, 0.0	0	NS	NS	NS
Continuous variables									
	Weaning age (d)	88	26.0 (3.8)	26.0	23.0, 29.0	0	NS	NS	NS
	WGT 1 at weaning (kg)	87	7.6 (1.3)	7.4	6.6, 8.6	1	0.009	NS	NS
	WGT 2 at 48 days post-weaning (kg)	83	31.8 (2.4)	31.6	30.3, 33.2	5	NS	NS	NS
	WGT 3 at 75 days post-weaning (kg)	76	53.5 (3.3)	53.6	51.8, 55.8	12	NS	NS	NS
	Growth rate from WGT 2 to WGT 3 (g/d)	74	805 (73)	806	760, 856	14	NS	NS	NS
	Days to market (d)	88	108.3 (3.1)	108.3	106.7, 109.7	0	<0.001	0.002	NS
	Age at market (d)	88	134.4 (3.9)	134.5	132.2, 137.0	0	NS	0.017	NS
	Live weight at market (kg)	88	81.5 (3.5)	81.7	79.3, 83.8	0	NS	0.011	NS

Unaccounted pigs: Pigs with move-in records, but without move-out records; WGT: Sample weight.

4.3.2.2 Missing values

Seventeen percent of the batches included at least one missing value. Missing values occurred exclusively in weight measurements. 'WGT 1', 'WGT 2' and 'Growth rate WGT 2 to WGT 3' were missing for 1.1%, 5.7% and 15.9% of the batches. The missing value pattern (Figure 4.3.1) does not indicate strong clustering of missing values over time.

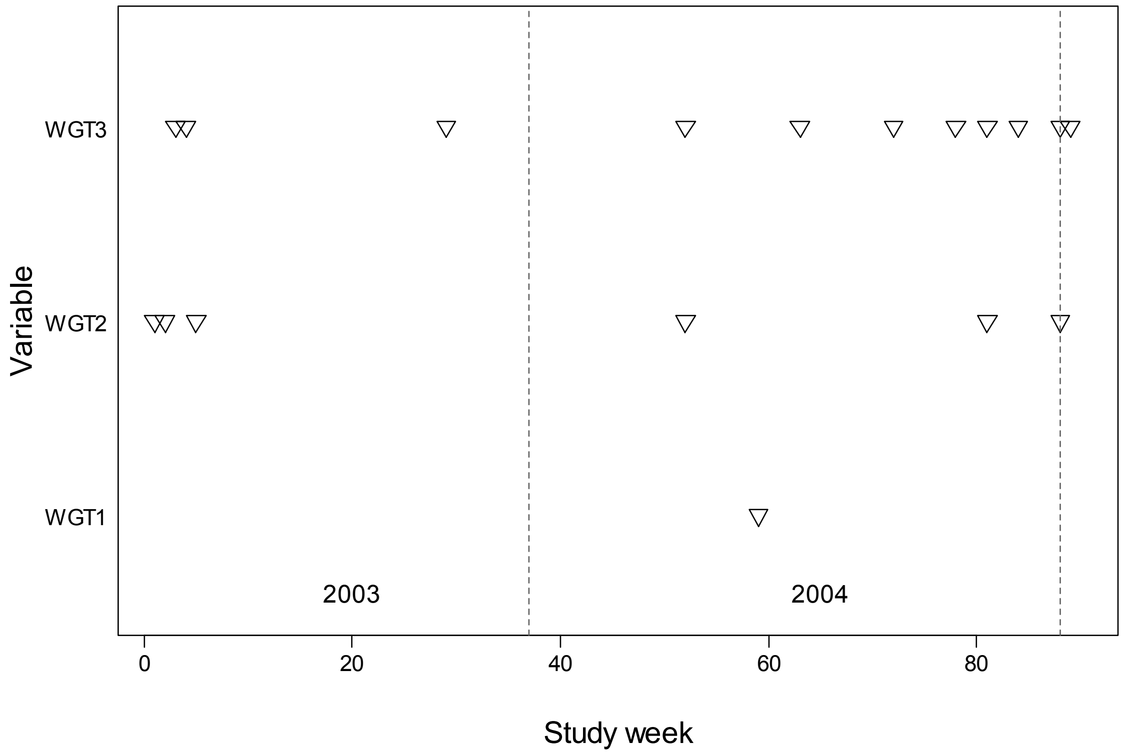

Figure 4.3.1. Missing value pattern of selected variables on pig farm C. Study week identifies batches (n = 88) weaned weekly between 5 June 2003 and 17 February 2005. Dashed lines separate subsequent years. WGT 1: Sample weight at weaning; WGT 2: Sample weight at 48 days post-weaning; WGT 3: Sample weight at 78 days post-weaning.

4.3.2.3 Breeding herd parameters

Farm C started monitoring breeding herd records after commencement of the study. The proportion of weekly piglet numbers recorded as weaned (source: PigLITTER®) compared to those recorded as entering a grower batch (source: PigGAIN®) were plotted over time (Figure 4.3.2) to evaluate when the breeding herd data set could be considered as complete. Up to study week 42 (phase 1), the proportion of weaned piglets recorded in PigLITTER® gradually increased. Thereafter (phase 2), weaned piglets recorded in PigLITTER® contributed almost 100% to the weaning batch (one outlier in study week 60). Batches in study week 42 were weaned on 27 March 2004.

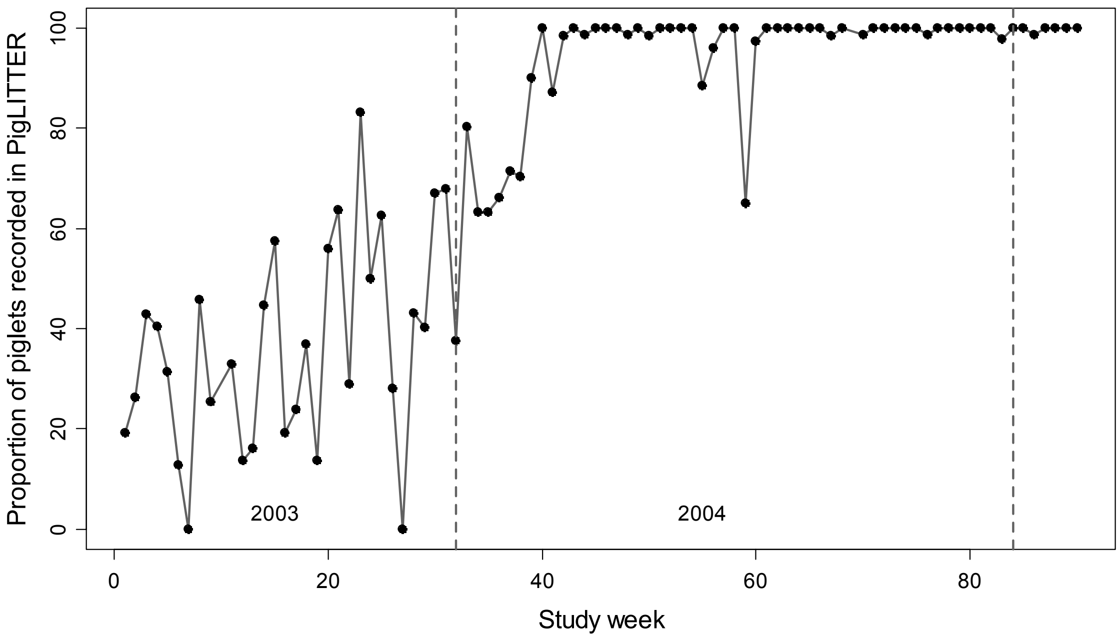

Figure 4.3.2. Time series plot of proportion of weekly piglet numbers recorded as weaned (source: PigLITTER®) compared to those recorded as entering a grower batch (source: PigGAIN®) on pig farm C. Study week identifies batches (n = 88) weaned weekly between 5 June 2003 and 17 February 2005. Dashed lines separate subsequent years.

Assuming that lifetime records for gilts entering the breeding herd had been entered into PigLITTER® throughout the study period, the 'Percentage of gilts farrowed' (Figure not shown) was considered in multivariable analysis. Although other breeding herd parameters were not included in multivariable analysis, descriptive statistics were performed (Table 4.3.2) to allow comparisons to the other farms.

Table 4.3.2. Descriptive statistics of breeding herd parameters for batches (n = 47) weaned weekly between 27 March 2004 and 17 February 2005 on pig farm C.

	Min	Q1	Median	Q3	Max
Pre-weaning mortality rate	0.0	5.0	8.5	13.3	31.0
Median parity of sows weaned (excl. gilts)	2.0	3.0	4.5	6.0	9.5
Coefficient of variation in weaning age (%)	0.0	7.8	11.8	15.4	28.2
Median number of piglets weaned per sow	7.5	9.0	10.0	10.5	12.0

4.3.2.4 Entry parameters

A median number of 77.5 piglets entered a batch. The time patterns of 'Entry numbers' is illustrated in Figure 4.3.3. Whilst 'Entry numbers' were relatively unstable up to study week 15 with a coefficient of variation (CV) of 10.5% (median: 74.5 pigs), variation in 'Entry numbers' was low between study weeks 16 and 50 (median: 77.0 pigs, CV: 6.6%). Thereafter variation increased again (median: 78.0, CV: 11.6%) with 'Entry numbers' ranging between 57 and 94 pigs.

Median weaning age was 26 days. The main feature of weaning age is its high variability over time (Figure 4.3.4). Weaning age tended to decrease in 2003 followed by a sharp increase at the turn of the year 2003/2004. Subsequently, weaning age decreased showing large variation especially in the second half of 2004. 'Weaning age' appeared more variable for batches weaned in summer and winter compared to batches weaned in spring and autumn (Figure 4.3.5).

Double weaning events (weaning of two batches within one week) and weaning breaks (week with no weaning event) had an impact on time patterns of weaning age. On the one hand, 'Weaning age' increased prior to double weaning events (Figure 4.3.4, encircled points). On the other hand, 'Weaning age' increased by approximately six to seven days in weeks following a week with no weaning event compared to the week prior to that (Figure 4.3.4, stars).

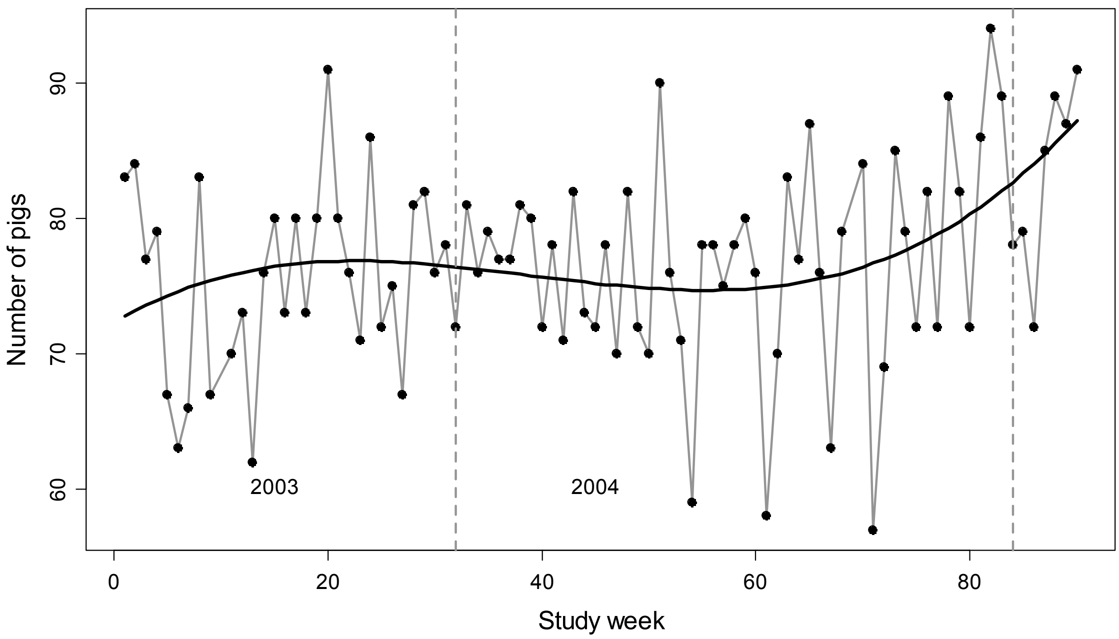

Figure 4.3.3. Time series plot of number of pigs entering batches on pig farm C. Study week identifies batches (n = 88) weaned weekly between 5 June 2003 and 17 February 2005. Black line illustrates a fitted 3rd order polynomial trend line (F = 4.79, DF = 3, P =0.004). Dashed lines separate subsequent years.

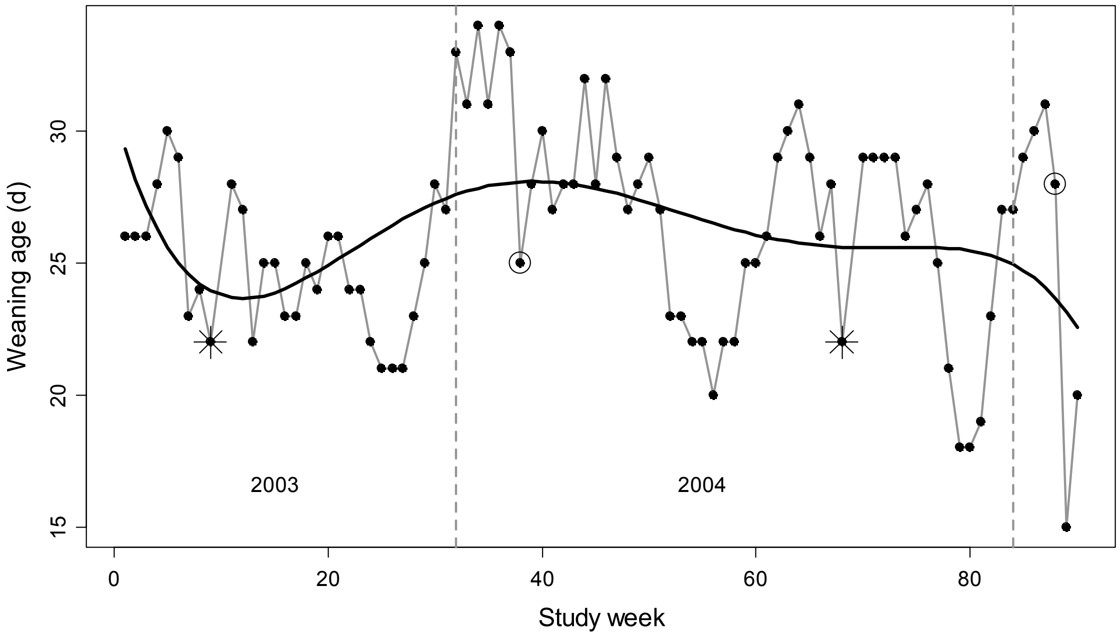

Figure 4.3.4. Time series plot of ‘Weaning age’ on pig farm C. Study week identifies batches (n = 88) weaned weekly between 5 June 2003 and 17 February 2005. Black line illustrates a fitted 5th order polynomial trend line (F = 2.68, DF = 5, P =0.027). Dashed lines separate subsequent years. Encircled data points present study weeks with double weaning events and stars identify weeks preceding a study week with no weaning event.

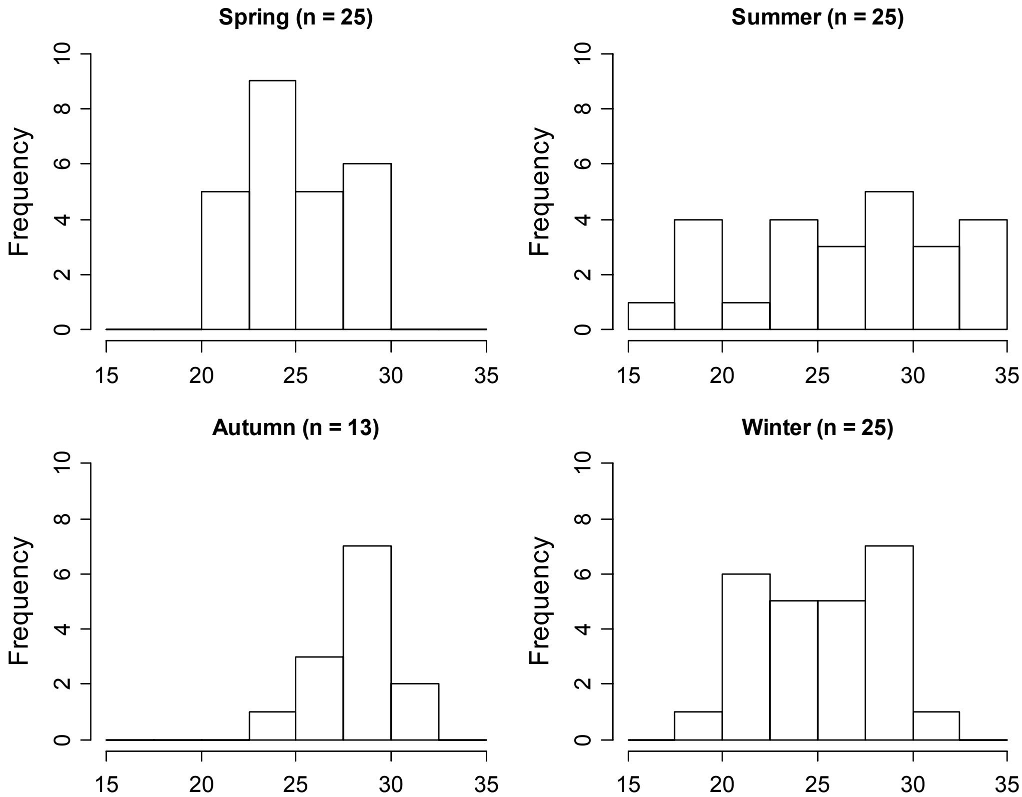

Figure 4.3.5. Histogram of weaning age stratified by season on pig farm C. The dataset included 88 batches weaned weekly between 5 June 2003 and 17 February 2005.

4.3.2.5 Deaths and sick pig movements

A total number of 104 deaths (across 75 batches) was recorded, of which 59.6% (across 41 batches) occurred at the weaner stage, 26.9% (across 21 batches) at the grower stage and 13.5% (across 13 batches) at the finisher stage.

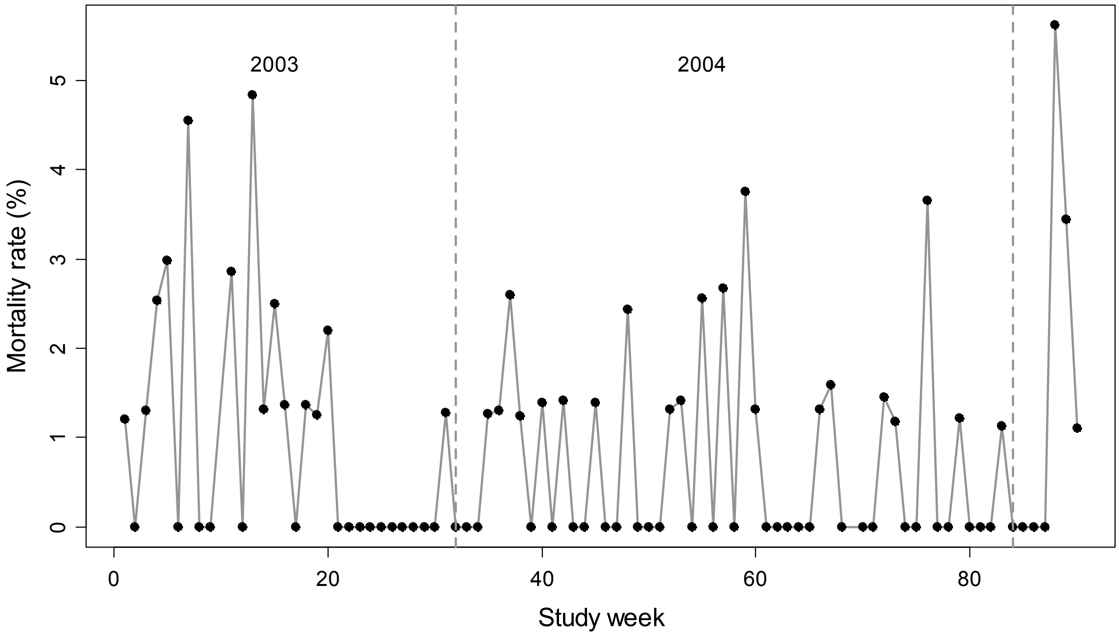

Figure 4.3.6. Time series plot of 'Weaner mortality rate' on pig farm C. Study week identifies batches (n = 88) weaned weekly between 5 June 2003 and 17 February 2005. Dashed lines separate subsequent years.

In mid 2003, there was a cluster of high weaner mortality rate (Figure 4.3.6). After a cluster of 12 weeks with zero weaner deaths at the end of 2003, a relatively stable period followed in year 2004. The maximum weaner mortality of 5.6% was observed in study week 88, which coincided with the minimum observed weaning age of 18 days.

There was no significant trend over time in grower deaths (Figure not shown). A cluster of zero grower deaths occurred during a twenty-week period in 2003. The maximum mortality rate of 3.8% was observed in study week 56.

Finisher deaths occurred sporadically throughout the study period (Figure not shown). One cluster with one to two finisher deaths in four out of five subsequent batches was identified at the end of 2004 (study weeks 82 to 86).

4.3.2.6 Unaccounted pigs

Fourteen pigs did not have move-in records (negative value for unaccounted pigs) and 90 pigs did not have move-out records (positive value for unaccounted pigs). From the latter ones, 53% were missing at the end of the weaner stage, 17% at the end of the grower stage and 30% at the end of the finisher stage. 'Percentage of unaccounted pigs' did not change over time at any production stage.

4.3.2.7 Sample weights

The proportion of the batch weighed was 26.6% (IQR: 24.2 – 35.2%) at weaning and 38.0% (IQR: 36.1 – 39.5%) at the grower and finisher stage. Mean 'Sample weight 1' (WGT 1) was 7.6 kg and mean 'Sample weight 2' (WGT 2) was 31.8 kg. Mean 'Growth rate WGT 2 to WGT 3' was 805 g/d. The grower/finisher growth rate from 48 days post-weaning to market was 824 g/d.

Figure 4.3.7 presents the batch-specific growth curves (by age) from 'Sample weight 1' to the final weight measurement stratified by 6-month periods. In contrast to farms A and B, age was chosen on the time axis due to high fluctuations in weaning age. Variation within and between strata appeared to be low. The figure indicates that pigs grew at a similar rate during the grower and the finisher stage.

Time patterns of sample weight measures are presented in Figure 4.3.8 to Figure 4.3.10. Variation in 'Sample weight 1' was lowest in 2003. In 2004 and 2005, 'Sample weight 1' showed similar time patterns as weaning age with low values in mid 2004 and at the end of 2004 and clusters of higher values in-between. Neither 'Sample weight 2' nor 'Growth rate WGT 2 to WGT 3' changed significantly over time. 'Growth rate WGT 2 to WGT 3' included one outlier in study week 46 with 564 g/d.

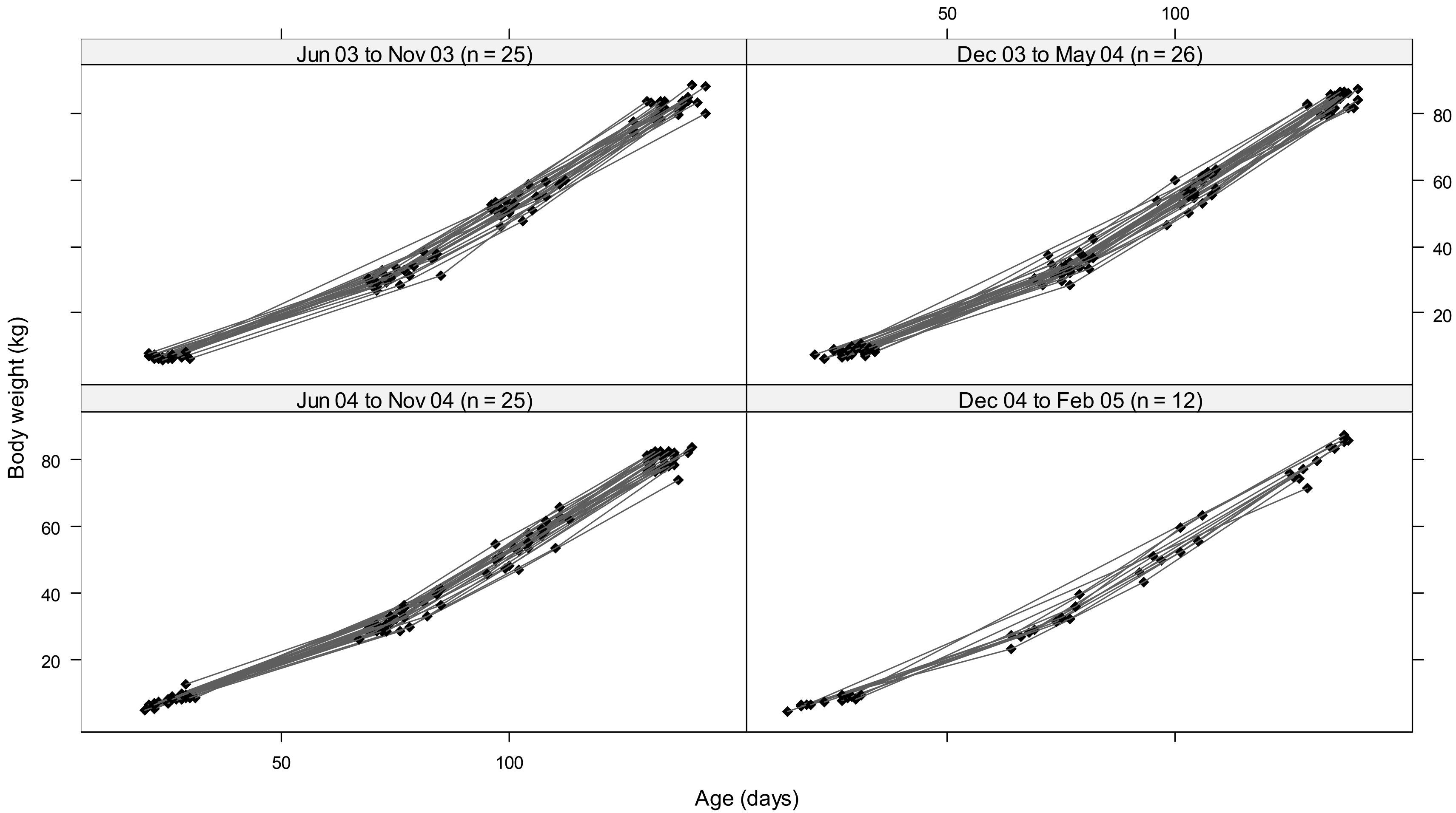

Figure 4.3.7. Batch-specific growth curves from weaning until market of batches (n = 88) weaned weekly between 5 June 2003 and 17 February 2005 on farm C. Batches were stratified by six-month periods.

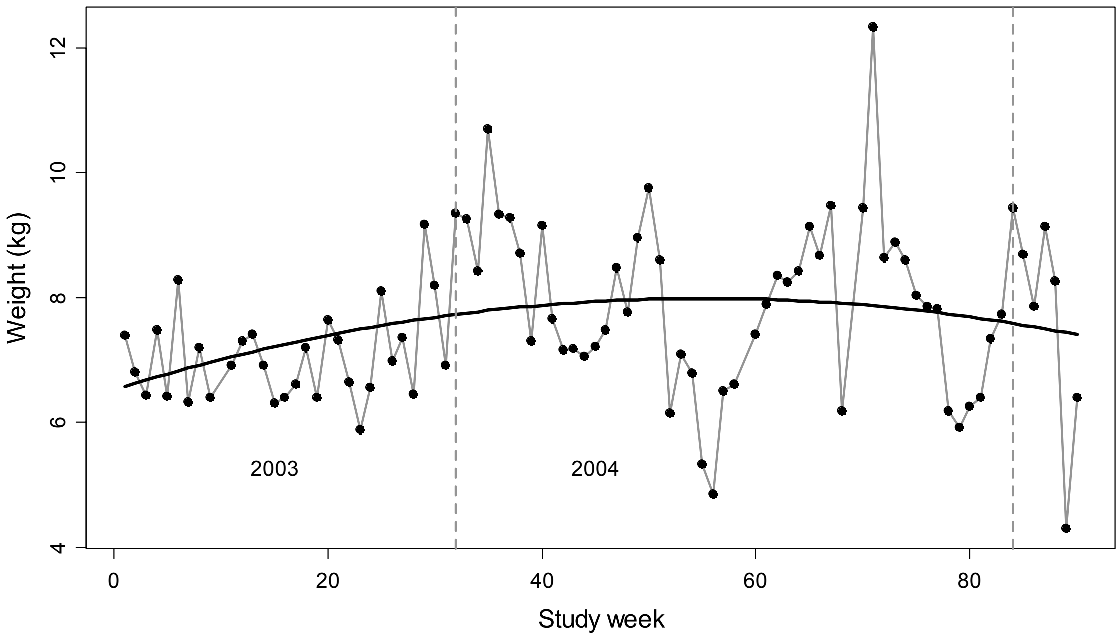

Figure 4.3.8. Time series plot of ‘Sample weight 1’ (day 0 post-weaning) on pig farm C. Study week identifies batches (n = 87) weaned weekly between 5 June 2003 and 17 February 2005. Black line illustrates a fitted a quadratic trend line (F = 3.86, DF = 2, P = 0.025). Dashed lines separate subsequent years.

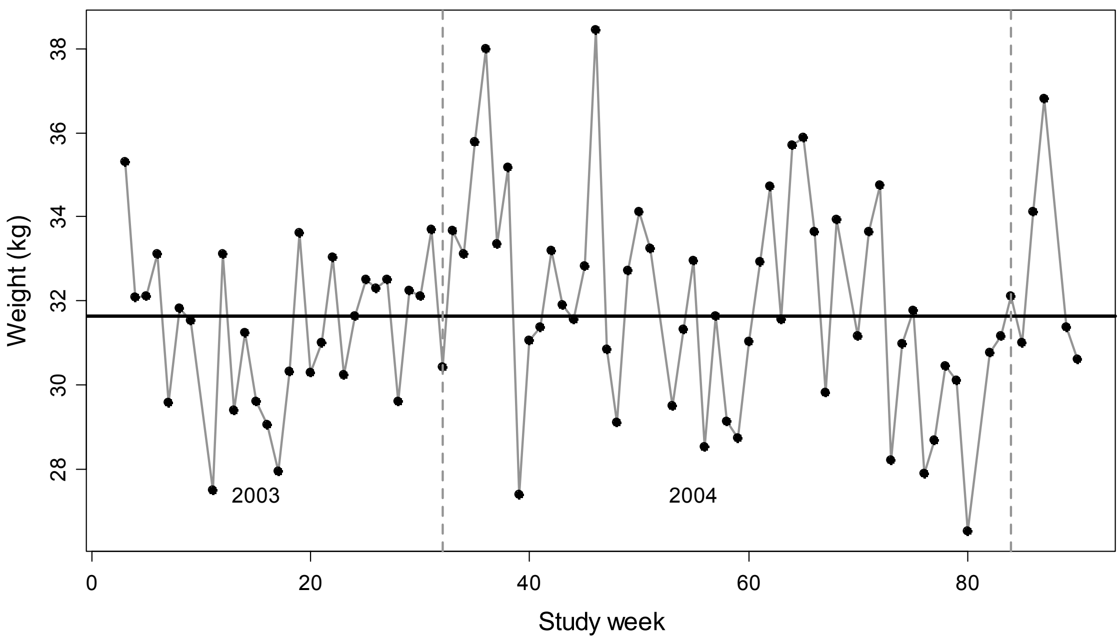

Figure 4.3.9. Time series plot of ‘Sample weight 2’ (day 48 post-weaning) on pig farm C. Study week identifies batches (n = 83) weaned weekly between 5 June 2003 and 17 February 2005. Black line illustrates the median level of ‘Sample weight 2’. Dashed lines separate subsequent years.

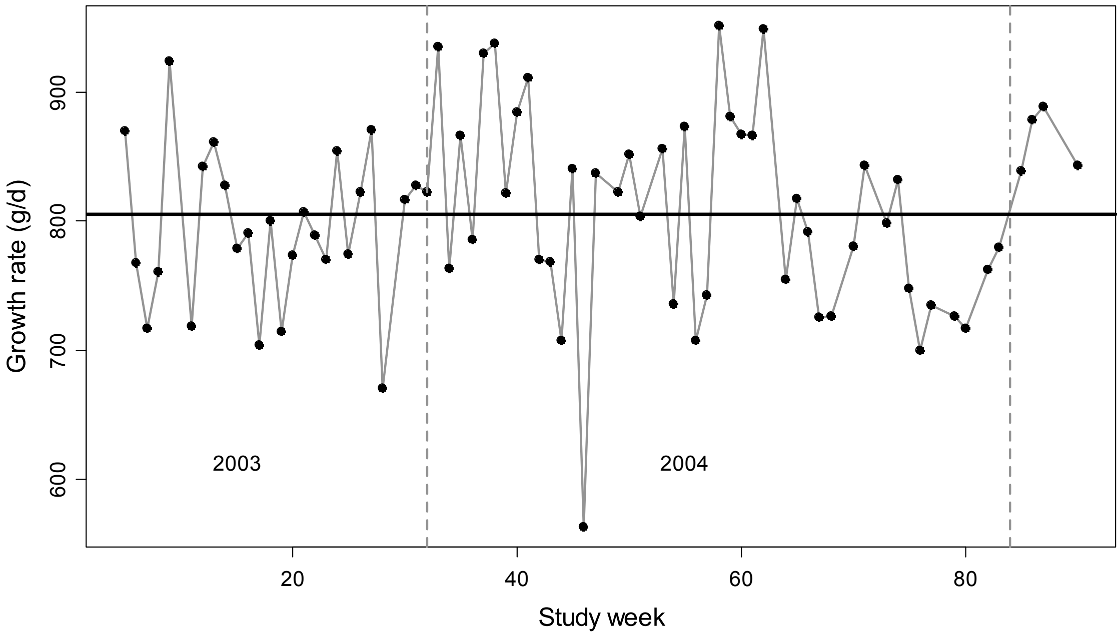

Figure 4.3.10. Time series plot of growth rate from sample weight 2 (day 48 post-weaning) to sample weight 3 (day 75 post-weaning) on pig farm C. Study week identifies batches (n = 74) weaned weekly between 5 June 2003 and 17 February 2005. Black line illustrates the median level of growth rate. Dashed lines separate subsequent years.

4.3.2.8 Market parameters

Batches were sold at a mean time of 108.3 d post-weaning and at a mean weight of 81.5 kg. Mean daily growth rate from birth to market was 595 g/d (based on the mean market age of 134.4 d). 'Market weight' (Figure 4.3.11) showed a significant downward trend (P = 0.02) indicating a decrease in 'Market weight' of 0.034 kg (SE ± 0.014 kg) per week. The downward trend appeared to be predominantly present throughout the year 2004.

The first nine batches were sold four to six days later than batches of the remaining study period (Figure 4.3.12). Earlier sales events during study week 12 to 15 and during study weeks 62 to 65 coincided with sales dates around Christmas. Batches sold earlier in the beginning of 2004 were the batches with the highest weaning age of the entire study period.

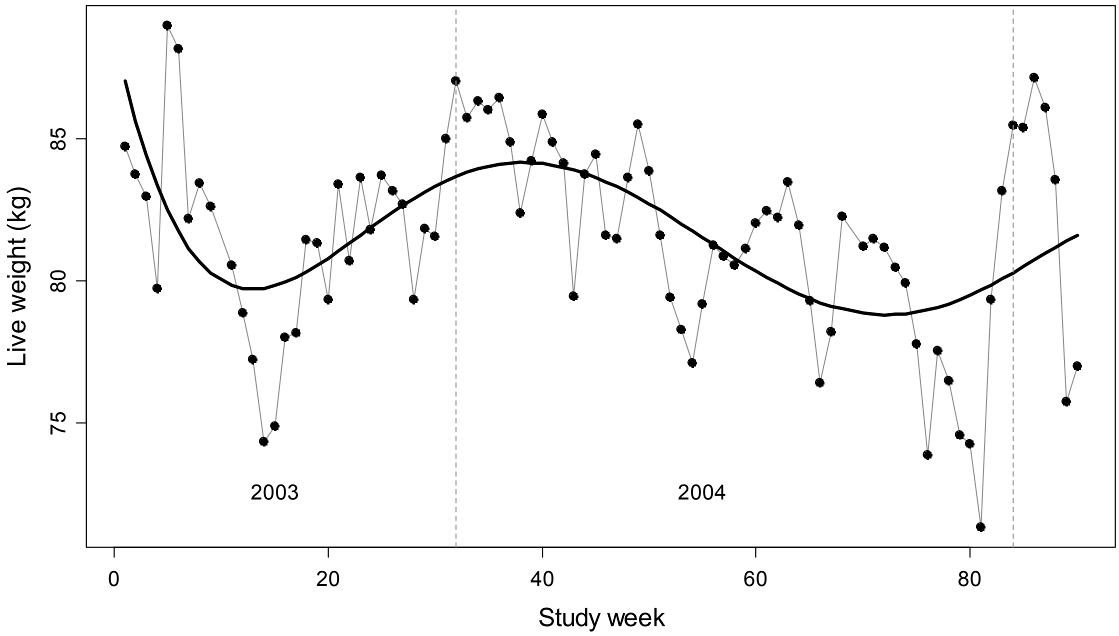

Figure 4.3.11. Time series plot of 'Market weight' on pig farm C. Study week identifies batches (n = 88) weaned weekly between 5 June 2003 and 17 February 2005. Black line illustrates a fitted 5th order polynomial trend line (F = 6.76, DF = 5, P < 0.001). Dashed lines separate subsequent years.

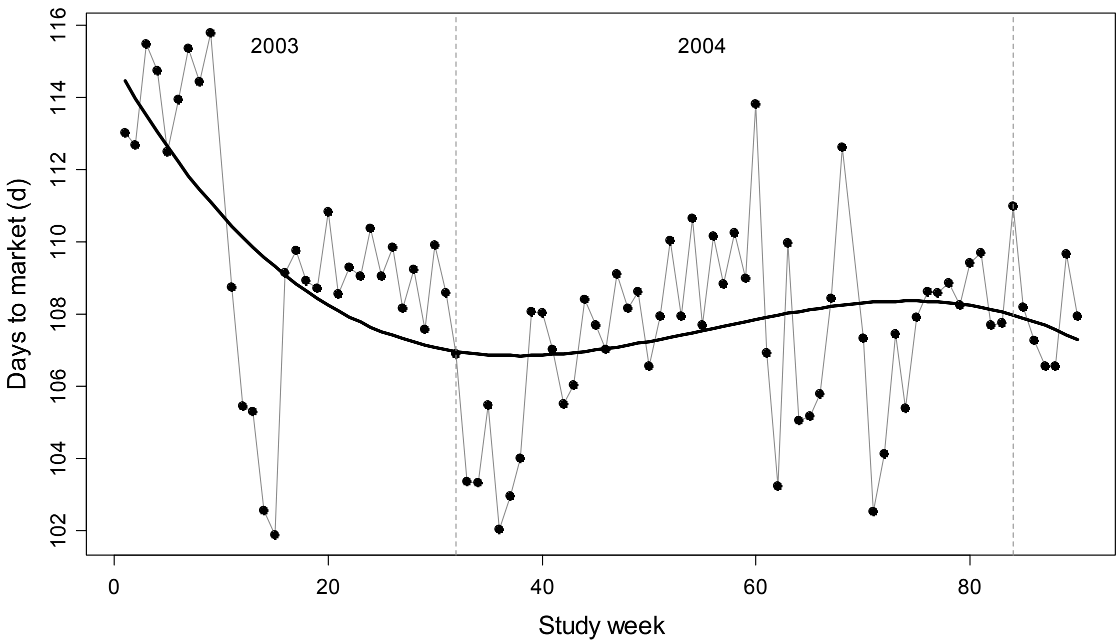

Figure 4.3.12. Time series plot of 'Days to market' on pig farm C. Study week identifies batches (n = 88) weaned weekly between 5 June 2003 and 17 February 2005. Black line illustrates a fitted 3rd order polynomial trend line (F = 11.3, DF = 3, P < 0.001). Dashed lines separate subsequent years.

4.3.2.9 Feed parameters

Feed intake data were not recorded on farm C.

4.3.3 *Univariable time series analysis*

The autocorrelation pattern of market weight is presented in Figure 4.3.13. The Autocorrelation Function (ACF) decayed slowly whilst the Partial Autocorrelation Function (PACF) died out after lag 1. This pattern is typical for a time series following a first-order autoregressive process with positive autocorrelation. Autocorrelations of the detrended series (Figure 4.3.14) were slightly lower than of the raw series.

As suspected from the ACF and PACF, backward elimination of autoregressive terms resulted in a first-order autoregressive term (AR1: -0.72 ± 0.08, $P < 0.001$). This model explained 49.8% of the overall variance in market weight as indicated by the total R-square. Residuals of this univariable autoregressive model showed remaining positive autocorrelation at lags 13 to 15 ($P < 0.01$).

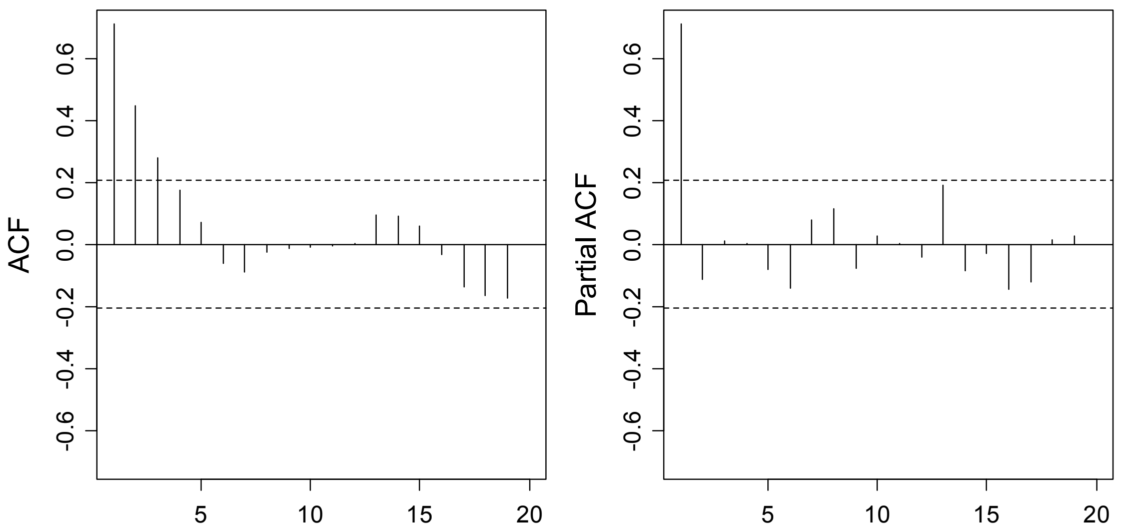

Figure 4.3.13. Autocorrelation function (ACF) and partial autocorrelation function (Partial ACF) for market weight on pig farm C. The dataset included records for 88 batches weaned between 5 June 2003 and 17 February 2005. Two missing observations were imputed. Dashed lines indicate 5% significance level that autocorrelation is zero. The lag order is specified on the horizontal axis, whilst estimated autocorrelations are shown on the vertical axis.

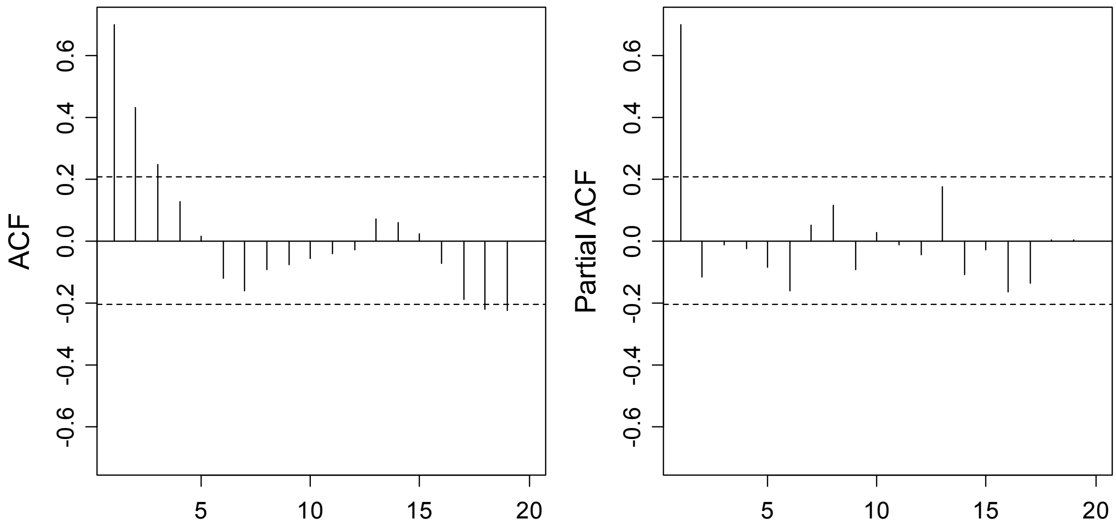

Figure 4.3.14. Autocorrelation function (ACF) and partial autocorrelation function (Partial ACF) for market weight after removal of the linear trend. The dataset included records for 88 batches weaned between 5 June 2003 and 17 February 2005 on pig farm C. Two missing observations were imputed. Dashed lines indicate 5% significance level that autocorrelation is zero. The lag order is specified on the horizontal axis, whilst estimated autocorrelations are shown on the vertical axis.

4.3.4 Collinearity between predictor variables

'Sample weight 2' was highly correlated with 'Sample weight 3' (r = 0.81), whereas its correlation with 'Growth rate WGT 2 to WGT 3' was low (r = 0.15). 'Weaning age' was moderately correlated with 'Age at market' (r = 0.69). Furthermore, 'Weaner mortality rate' was highly correlated with 'Overall mortality rate' (r = 0.75).

4.3.5 Univariable regression analysis with autoregressive error correction

Univariable analysis using a first-order autoregressive model resulted in nine variables with significance values less than 0.2 (Table 4.3.3). 'Weaning age' and 'Age at market' showed the strongest association with 'Market weight', exhibiting a positive effect. Similarly, 'Growth rate WGT 2 to WGT 3', 'WGT 1' and 'WGT 2' were positively associated with 'Market weight'. In contrast, 'Entry numbers' and 'Weaner mortality rate' showed a negative association with 'Market weight'. Trend ('Study week') and 'Season', both presenting time features, showed only weak associations with 'Market weight'.

Table 4.3.3. Predictor variables associated with market weight of 88 batches of pigs weaned between 5 June 2003 and 17 February 2005 on farm C. Variables were tested for associations using a first-order autoregressive model. The first-order autoregressive term was highly significant ($P < 0.001$) for all variables. Regression coefficients ('Beta') and their standard errors ('SE') are reported. The Regression R^2 (Regr. R^2) indicates the accuracy of the structural part of the model after autoregressive transformation.

Variable	Category	Beta	SE	P-value	Regr. R^2
Weaning age (d)		0.39	0.09	<0.001	0.19
Age at market (d)		0.35	0.08	<0.001	0.17
WGT 2 (kg)		0.25	0.11	0.03	0.06
Entry numbers		-0.062	0.030	0.05	0.05
WGT 1 (kg)		0.45	0.23	0.06	0.04
Season of weaning	Spring: Sep to Nov	REF		0.16	0.04
	Summer: Dec to Feb	0.58	1.46		
	Autumn: Mar to May	2.73	1.94		
	Winter: Jun to Aug	2.04	1.44		
Growth rate WGT 2 to WGT 3 (g/d)		0.0042	0.0029	0.16	0.02
Study week		-0.041	0.031	0.19	0.02
Weaner mortality rate (%)		-0.22	0.17	0.19	0.02

REF: Reference category; WGT 1: Entry weight weaner stage (day 0 post-weaning); WGT 2: Entry weight grower stage (day 48 post-weaning); WGT 3: Entry weight finisher stage (day 75 post-weaning).

4.3.6 Multivariable regression analysis with autoregressive error correction

It was attempted to include 'Days to market' instead of 'Age at market' in the full model to avoid collinearity between 'Weaning age' and 'Age at market'. Although 'Days to market' was not significant in the univariable model ($P = 0.83$), this parameter was highly significant in the full model ($P < 0.001$), which also accounted for the effect of 'Weaning age'. Since, inclusion of 'Days to market' considerably enhanced the significance of 'Weaning age' whilst having minimal effect on other parameters, 'Days to market' was kept in the model instead of 'Age at market'. The results of the multivariable regression model for 'Market weight' with adjustment for autocorrelation are presented in Table 4.3.4. The first-order autoregressive term was highly significant ($P < 0.001$). The significant interaction between 'Weaning age' and 'Season' is graphically displayed in Figure 4.3.15. 'Weaning age' had a positive effect on 'Market weight' in all seasons apart from spring.

Table 4.3.4. Final autoregressive model for risk factors associated with market weight of 88 batches of pigs weaned between 5 June 2003 and 17 February 2005 on farm C. Regression coefficients ('Beta') and their standard errors ('SE') are reported.

Variable	Category	Beta	SE	P-value
Entry numbers		-0.075	0.028	0.009
WAGE (d)		-0.051	0.186	0.79
WGT 2 (kg)		0.27	0.10	0.010
Growth rate WGT 2 to WGT 3 (g/d)		0.0072	0.0026	0.007
DTM (d)		0.35	0.10	0.001
Season of weaning	Spring: Sep to Nov	REF		0.002
	Summer: Dec to Feb	-15.57	4.93	
	Autumn: Mar to May	-8.22	8.08	
	Winter: Jun to Aug	-12.06	6.27	
WAGE x Season	AGE x Spring	REF		<0.001
	AGE x Summer	0.70	0.20	
	AGE x Autumn	0.39	0.30	
	AGE x Winter	0.51	0.25	
AR1		-0.39	0.12	<0.001

REF: Reference category; WAGE: Weaning age; WGT 2: Entry weight grower stage (day 48 post-weaning); WGT 3: Entry weight finisher stage (day 75 post-weaning); DTM: Days to market; AR1: First-order autoregressive term.
Intercept = 34.5, Regression R^2 = 0.578, Total R^2 = 0.750, Log-likelihood = -174.9, DF = 13, P < 0.001.

Residuals from the autoregressive model were normally distributed (P > 0.15) and homoscedastic (P > 0.15) with no remaining autocorrelation (P > 0.15). The models resulted in residuals greater than 3.3 for seven study weeks (study weeks 4, 5, 21, 23, 30, 56 and 81), and the maximum absolute residual was 4.7 (study week 5) (Figure 4.3.16). No possible explanation for outliers was found for any of the observations. Deletion of observation 5 decreased the autoregressive coefficient for the AR1 term by 0.69 times the standard error. The effect on other parameters and the effect of deleting the other outliers changed parameter estimates by less than half their standard error. As no sensible explanation could be found for large residuals, no observation was excluded from the analysis.

When fitting the selected model to the dataset with non-imputed missing values, parameter estimates of 'Days to market' increased by 0.62 times the standard error. Furthermore, the first-order autoregressive term decreased by 0.53 times the standard error. Changes in other parameter estimates were minimal. Neither the exclusion of outliers nor fitting of the model to the complete dataset affected the sign of any of the parameter estimates.

Residuals from the autoregressive model appeared to follow a first-order autoregressive process since the ACF slowly decayed and the PACF dropped off after lag 1 (Figure 4.3.17).

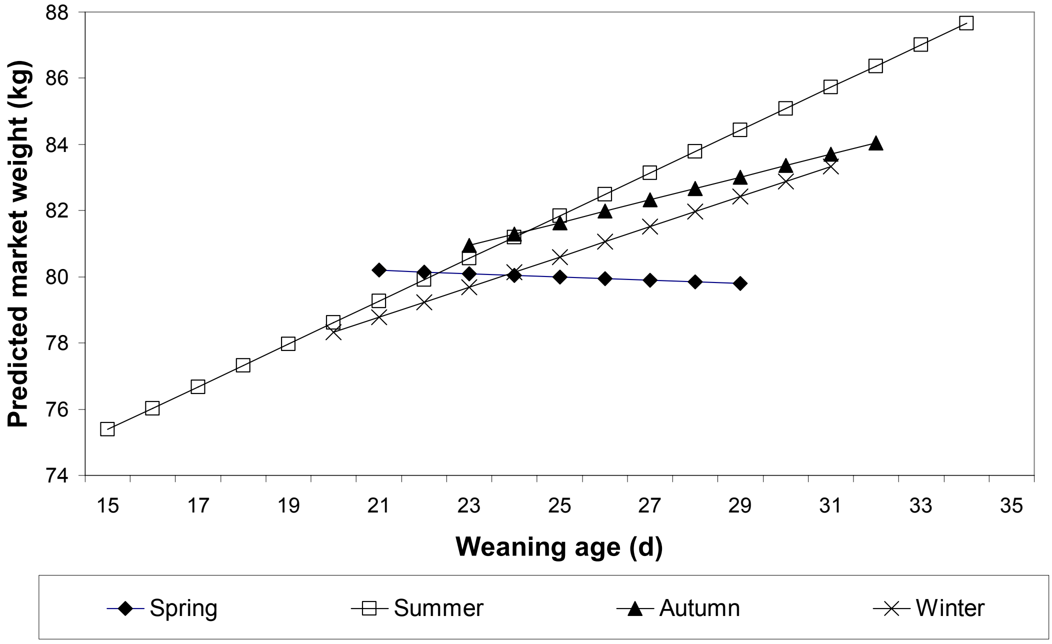

Figure 4.3.15. Graphical illustration of the interactive effect between ‘Weaning age’ and ‘Season’ on predicted values of market weight derived from the autoregressive model on farm C. All other model parameters were fixed in the model at their median value. The range in weaning ages relates to the observed ranges in weaning ages per season.

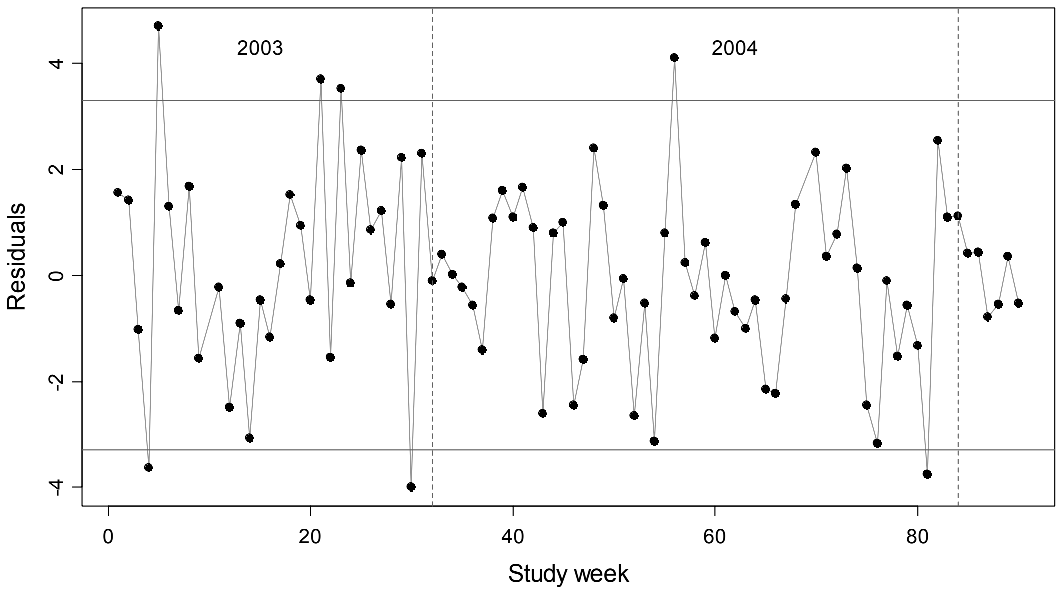

Figure 4.3.16. Time series plot of standardized residuals from the autoregressive model to predict market weight of batches of pigs on farm C. Study week identifies batches (n = 88) weaned weekly between 5 June 2003 and 17 February 2005. Horizontal lines indicate threshold values for standardized residuals exceeding ± 3.3. Dashed vertical lines separate subsequent years.

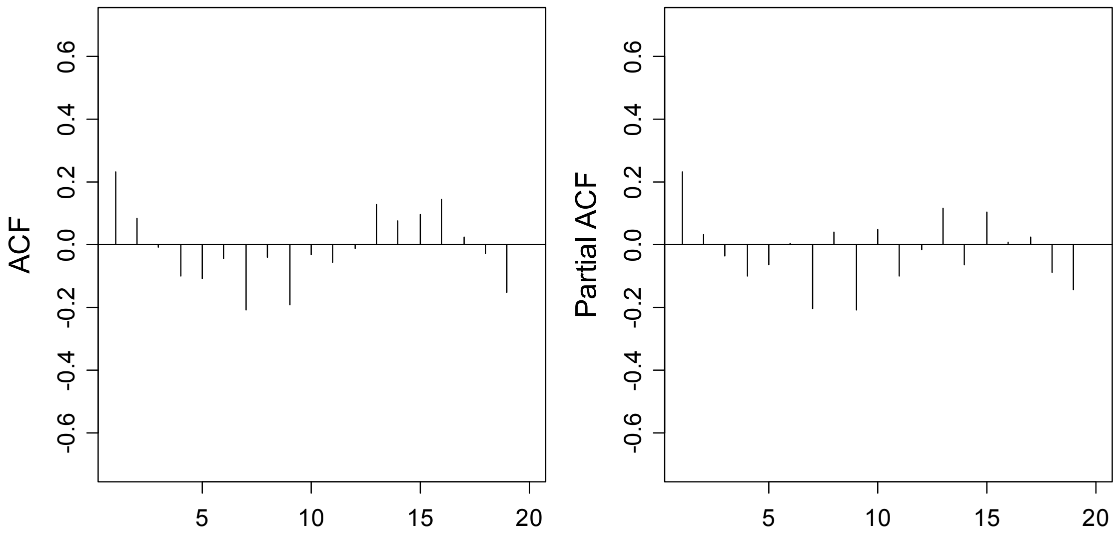

Figure 4.3.17. Autocorrelation function (ACF) and partial autocorrelation function (Partial ACF) of untransformed model residuals on pig farm C. The data set included records for 88 batches weaned between 5 June 2003 and 17 February 2005. Two missing observations were imputed. The lag order is specified on the horizontal axis, whilst estimated autocorrelations are shown on the vertical axis.

4.3.7 Univariable ordinary least squares regression analysis

Univariable screening resulted in nine parameters selected for the full multivariable ordinary least squares (OLS) regression model (Table 4.3.5). 'Weaning age', 'Age at market', 'Sample weight 1', 'Sample weight 2' and 'Growth rate WGT 2 to WGT 3' showed strong positive associations with 'Market weight'. Furthermore, univariable screening indicated that batches weaned in spring were significantly lighter at market than batches weaned in other seasons. The negative effect of 'Study week' indicated a downward trend in 'Market weight'.

Table 4.3.5. Predictor variables associated with market weight of 88 batches of pigs weaned between 5 June 2003 and 17 February 2005 on farm C. Variables were tested for associations using ordinary least squares regression analysis. Regression coefficients ('Beta') and their standard errors ('SE') as well as the coefficient of determination ('R^2') are reported.

Variable	Category	Beta	SE	P-value	R^2
Age at market (d)		0.58	0.08	<0.001	0.41
Weaning age (d)		0.55	0.08	<0.001	0.35
WGT 2 (kg)		0.68	0.13	<0.001	0.22
WGT 1 (kg)		1.06	0.27	<0.001	0.14
Season of weaning	Spring: Sep to Nov	REF		0.004	0.09
	Summer: Dec to Feb	2.64	0.95		
	Autumn: Mar to May	3.42	1.15		
	Winter: Jun to Aug	2.08	0.95		
Growth rate WGT 2 to WGT 3 (g/d)		0.0108	0.0043	0.013	0.06
Study week		-0.034	0.014	0.020	0.05
Overall mortality rate (%)		-0.51	0.25	0.046	0.03
Entry numbers		-0.072	0.050	0.151	0.01

REF: Reference category; WGT 1: Entry weight weaner stage (day 0 post-weaning); WGT 2: Entry weight grower stage (day 48 post-weaning); WGT 3: Entry weight finisher stage (day 75 post-weaning).

4.3.8 Multivariable ordinary least squares regression analysis

Similar to the autoregressive model, inclusion of 'Days to market' instead of 'Age at market' considerably improved the significance of 'Weaning age' in the multivariable model. The final ordinary least squares (OLS) regression model is presented in Table 4.3.6.

Residuals were normally distributed ($P > 0.15$) and homoscedastic ($P > 0.15$). The Durbin-Watson test statistic indicated significant autocorrelation of residuals at lag 1 ($P = 0.006$) and marginally significant autocorrelation at lags 2 ($P = 0.053$) and 15 ($P = 0.090$).

The models resulted in residuals greater than 3.3 for seven study weeks (study weeks 4, 5, 23, 30, 56, 76 and 81). The maximum absolute residual was 4.5 (study week 76). Exclusion of any of these residuals neither changed the sign of parameter estimates nor altered the magnitude of parameter estimates by more than 0.6 times the standard error (SE).

Fitting the model to the complete dataset (excluding observations with missing values) did not change the sign of parameter estimates. However, the magnitude of estimates changed considerably for 'Growth rate WGT 2 to WGT 3' (-1.2 times SE) and 'Days to market' (-0.9 times SE).

Table 4.3.6. Final ordinary least squares regression model for risk factors associated with market weight of 88 batches of pigs on farm C. Batches were weaned between 5 June 2003 and 17 February 2005. Regression coefficients (‘Beta’) and their standard errors (‘SE’) are reported.

Variable	Category	Beta	SE	P-value
WAGE (d)		0.062	0.165	0.71
WGT 2 (kg)		0.33	0.10	0.002
Growth rate WGT 2 to WGT 3 (g/d)		0.0106	0.0028	<0.001
DTM (d)		0.53	0.09	<0.001
Season of weaning	Spring: Sep to Nov	REF		0.001
	Summer: Dec to Feb	-15.64	4.64	
	Autumn: Mar to May	-10.48	8.46	
	Winter: Jun to Aug	-7.59	5.38	
WAGE x Season	AGE x Spring	REF		<0.001
	AGE x Summer	0.68	0.18	
	AGE x Autumn	0.46	0.31	
	AGE x Winter	0.31	0.21	

REF: Reference category; WAGE: Weaning age; WGT 2: Entry weight grower stage (day 48 post-weaning); WGT 3: Entry weight finisher stage (day 75 post-weaning); DTM: Days to market.
Intercept = 2.4, Adj. $R^2 = 0.705$, F = 18.4, DF = 11, P < 0.001.

4.3.9 Model comparison

In comparison to the first-order autoregressive (AR1) model, the ordinary least squares (OLS) regression model included one less main effect (Table 4.3.7). Residual autocorrelation was present in the OLS regression model, but not in the autoregressive model.

The OLS regression model and the structural part of the AR-model accounted for 71% and 58% of the overall variance in ‘Market weight’, respectively. In contrast, the structural and autoregressive part of the AR-model enabled to predict observations with greater accuracy than the OLS-model (Total $R^2 = 0.75$).

Parameters selected in the AR1 model were fitted to the OLS-model (‘reduced model’) (Table 4.3.8). This reduced model yielded autocorrelated residuals at lag 1 (P = 0.003).

Table 4.3.7. Comparison of regression models for predictor variables associated with market weight of 88 batches of pigs weaned between 5 June 2003 and 17 February 2005 on farm C. Regression parameters were derived through ordinary least squares regression analysis (OLS) or regression analysis with autoregressive error correction (AR). Regression coefficients (‘Beta’) and their standard errors (‘SE’) are reported.

Type	Variable/parameter	Category	Beta (SE)	
			OLS	AR
Main effects				
	Intercept		2.4 (13.5)	34.5 (15.3)
	Entry numbers		-	-0.075 (0.028)
	WAGE (d)		0.062 (0.165)	-0.051 (0.186)
	WGT 2 (kg)		0.332 (0.104)	0.270 (0.103)
	Growth rate WGT 2 to WGT 3 (g/d)		0.0106 (0.0028)	0.0072 (0.0026)
	DTM (d)		0.529 (0.092)	0.353 (0.104)
	Season of weaning	Spring: Sep to Nov	REF	REF
		Summer: Dec to Feb	-15.64 (4.637)	-15.57 (4.93)
		Autumn: Mar to May	-10.48 (8.459)	-8.22 (8.08)
		Winter: Jun to Aug	-7.59 (5.376)	-12.06 (6.27)
Interactions				
	WAGE x Season	WAGE x Spring	REF	REF
		WAGE x Summer	0.68 (0.18)	0.70 (0.20)
		WAGE x Autumn	0.46 (0.31)	0.39 (0.30)
		WAGE x Winter	0.31 (0.21)	0.51 (0.25)
Autoregressive parameters				
	AR1		-	-0.39 (0.12)
Model fit				
	DF used		11	12 + 1
	Significant autocorrelations		Lag 1**	-
	Regression R^2		0.705	0.578
	Total R^2		0.705	0.750

REF: Reference category; WAGE: Weaning age; WGT 2: Entry weight grower stage (day 48 post-weaning); WGT 3: Entry weight finisher stage (day 75 post-weaning); DTM: Days to market; AR1: First-order autoregressive term; DF: degrees of freedom.

Significance values: * $P < 0.05$, ** $P < 0.01$, *** $P < 0.001$.

Table 4.3.8. Comparison of 'reduced' regression models for predictor variables associated with market weight of 88 batches of pigs weaned between 5 June 2003 and 17 February 2005 on farm C. Regression parameters were derived through ordinary least squares regression analysis (OLS) or regression analysis with autoregressive error correction (AR). Reduced model: Model parameters identified in the AR-model were fitted to the OLS-model. Regression coefficients ('Beta') and their standard errors ('SE') are reported.

Type	Variable/parameter	Category	Beta (SE)	
			OLS	AR
Main effects				
	Intercept		7.3 (13.2)	34.5 (15.3)
	Entry numbers		-0.074 (0.031)	-0.075 (0.028)
	WAGE (d)		0.019 (0.161)	-0.051 (0.186)
	WGT 2 (kg)		0.35 (0.10)	0.27 (0.10)
	Growth rate WGT 2 to WGT 3 (g/d)		0.0103 (0.0027)	0.0072 (0.0026)
	DTM (d)		0.54 (0.09)	0.35 (0.10)
	Season of weaning	Spring: Sep to Nov	REF	REF
		Summer: Dec to Feb	-15.81 (4.50)	-15.57 (4.93)
		Autumn: Mar to May	-9.94 (8.21)	-8.22 (8.08)
		Winter: Jun to Aug	-9.65 (5.29)	-12.06 (6.27)
Interactions				
	WAGE x Season	WAGE x Spring	REF	REF
		WAGE x Summer	0.70 (0.18)	0.70 (0.20)
		WAGE x Autumn	0.44 (0.30)	0.39 (0.30)
		WAGE x Winter	0.38 (0.21)	0.51 (0.25)
Autoregressive parameters				
	AR1		-	-0.39 (0.12)
Model fit				
	DF used		12	12 + 1
	Significant autocorrelations		Lag 1**	-
	Regression R^2		0.726	0.578
	Total R^2		0.726	0.750

REF: Reference category; WAGE: Weaning age; WGT 2: Entry weight grower stage (day 48 post-weaning); WGT 3: Entry weight finisher stage (day 75 post-weaning); DTM: Days to market; AR1: First-order autoregressive term; DF: degrees of freedom.
Significance values: * $P < 0.05$, ** $P < 0.01$, *** $P < 0.001$.

Chapter 5 Discussion

5.1 Introduction

This observational study aimed to identify performance parameters, which can be used to predict market weight of a batch of pigs on three commercial farms. Study periods included 140, 127 and 90 weeks on farms A, B and C, respectively. Each farm was investigated separately as study periods and available performance parameters varied between farms. Parameters considered in the study for at least one of the farms included breeding herd parameters, feed and weight measurements as well as pig counts (e.g. entry numbers, deaths) and time measures (e.g. entry age, days to market). Since we assumed that data were correlated over time, we compared two statistical approaches for the analysis of the data, an autoregressive model and an ordinary least squares regression model. Apart from section 5.3.6, all parameter estimates relate to the results from the (statistically more correct) autoregressive models

5.2 Methods

5.2.1 Observational study

An observational study was considered appropriate as we aimed to derive a model to predict market weight, which is applicable in the commercial environment. In commercial pig production, a complex web of many interrelated elements affects herd productivity and profitability. Research has widely investigated the response in production parameters to animal factors, nutrient supply, environmental conditions and disease (Quiniou et al. 1999; Van Milgen et al. 2000; Wellock et al. 2003). However, it is recognized that the animal's response is different in commercial environments compared to ideal conditions found in research environments (Dritz et al. 1997; Schinckel et al. 2002; Nyachoti et al. 2004). For instance, Holck (1998) showed that growth rate and protein accretion were approximately 30% lower in pigs raised on commercial operations than in pigs raised under "ideal" conditions. This is caused by a combination of various stressors occurring in the commercial environment, which were shown to have an additive effect (Hyun et al. 1998). Thus, empirical estimates derived from “non-limiting conditions” in a research environment cannot be directly applied to commercial situations.

Secondly, conducting an observational study enabled us to gather a large amount of data at a relatively low cost. Furthermore, the study design allowed us to include retrospective production data on farms A and B resulting in longer study periods. However, by including retrospective data we could not adjust and hence standardize the data collection protocol of the individual farms at study start. Consequently, the three farms showed differences in the variables they collected and the way they collected these variables. Accordingly, we developed separate models for each individual farm instead of creating an overall model with farm as a fixed effect. This was not considered a major disadvantage since the studied population of three farms would have been insufficient to generalize results to larger populations of interest, e.g. other New Zealand farms meeting inclusion criteria for enrolment in the study.

5.2.2 Unit of interest

We chose the batch as the unit of interest due to the following reasons: First, commercial pig production is predominantly concerned with batch performance, not with the performance of individual pigs. Secondly, farms in our study recorded most causative factors at the batch level. Thirdly, if the measuring unit was the pen (sample weights on farm B) or the individual pig (market weights on farms B and C), these measurement units were not identifiable throughout the production period. Therefore, no other causative factors could be used to differentiate between these measurement units. Aggregation of data recorded on the pen or individual pig level to the batch level led to a loss of information detail. However, due to the reasons outlined above, there would have been limited benefits in using pen and pig level data for answering the study question.

The fact that all farms applied split marketing raises a problem when using the batch as the unit of interest. ‘Days to market’ and ‘Market weight’ present the mean batch value derived from multiple sales events. This is particularly important when forecasting performance of future batches based on a mean value of ‘Days to market’. Following the mean sales date, the sales dates of each load of pigs needs to be adjusted versus the mean sales date given the routine marketing regime applied on the farm.

5.2.3 Outcome variable

Market weight was chosen as the variable of interest, because this parameter was available on all farms, either as carcass weight data recorded at the abattoir (farm A) or as live weight data recorded on-farm (farms B and C). Furthermore, the ability to forecast market weight is useful for pig producers in making management and marketing decisions. Alternatively, 'Growth rate' from birth or from weaning to market could have been chosen as the outcome variable as in the study of Madsen (2000). The calculation of this indirect parameter is based on 'Market weight' and 'Time to market'. This would have been effective in reducing time fluctuations of 'Market weight' as a univariable parameter. However, we were concerned about including the confounding effect of 'Time to market' on pig performance as a predictor variable in the multivariable model, since this parameter would then have been on both sides of the model equation. Furthermore, the effect of factors on 'Market weight' is easier to comprehend and can be interpreted in a more straightforward manner than the effect on 'Growth rate'.

5.2.4 Analytical methods

5.2.4.1 <u>Time series analysis</u>

We identified several analytical challenges in our dataset. First, since measurements were taken over time, these data were assumed to be autocorrelated and hence not independent. Secondly, distinct time patterns such as deterministic trend and seasonality may be present in the outcome variable causing the time series to be non-stationary. However, since we aimed to perform a multivariable analysis, we did not want to remove any of these time patterns a priori, since we did not know how much of the autocorrelation, trend and seasonality was explained by the predictor variables.

We chose a regression model with autoregressive error correction ('autoregressive model') as our analytical approach. This method is based on ordinary least squares regression. Consequently, it is easy to apply to datasets with a large number of predictors and can be performed using similar modelling strategies as in ordinary least squares regression analysis. However, the following assumptions need to be met to make this statistical approach valid.

First, the data need to be recorded in equally spaced time intervals. It was routine management on all our studied farms to manage pigs in weekly batches apart from few exceptions. If two batches were weaned within one week (farm C: n = 2), one of these batches was excluded from the analysis, since it was managed differently from the remainder of the batches. Furthermore, in weeks with no weaning event (farm A: n = 1; farm C: n = 2), a record was created with all parameters set as missing to obtain a continuous sequence of observations. As a result, recorded data were all equally spaced in time.

Secondly, the residual series of the multivariable analysis needs to be stationary, thus not including autocorrelation, trend or seasonality. We considered the effect of season and trend (‘Study week’) during model selection, so that these time factors could compete against other predictor variables. Finally, we assessed whether the residual series was stationary by testing it for linearity, remaining autocorrelation and homoscedasticity.

Thirdly, autoregressive error correction is only appropriate if the residual series follows an autoregressive and not a moving average (MA) or a mixed autoregressive-moving average (ARMA) process (Choudhury et al. 1999). The Autocorrelation Function (ACF) and the Partial Autocorrelation Function (PACF) were used to diagnose underlying autocorrelation patterns. As a preliminary step, we identified the autocorrelation pattern of the outcome variable. After multivariable analysis, we then confirmed whether untransformed residuals followed an autoregressive process.

5.2.4.2 Missing values

Missing values in predictor variables were imputed prior to multivariable regression analysis. Case wise deletion was not considered appropriate since this method introduces bias if more than 5% of the data are missing, and if values are not missing completely at random (Anderson et al. 1985; Acock 2005). Furthermore, case wise deletion would have interrupted the continuity of the time series, thus reducing the efficiency of time series estimates (Harvey et al. 1998; Junninen et al. 2004).

We used the ‘nearest neighbour’ (NN) technique to impute missing values, which implies that the nearest valid data point is used for imputation. This presents a relatively simple imputation method. Several authors showed that simple imputation techniques are appropriate if the percentage of observations with missing values is relatively small (< 10) (Barzi et al. 2004; Van der Heijden et al. 2006). We investigated whether imputation may have produced biased results by fitting the final model to the non-imputed data set and assessing changes in parameter estimates and significance values.

5.3 Results

5.3.1 Exclusion of batches

On farm A, the last 35 batches of the original dataset were excluded from analysis. Reasons for exclusion included (1) a change in weaning management (n = 12) and (2) occurrence of multiple missing values (n = 23). In the first case, a sample size of twelve out of 174 batches was not considered large enough to assess adequately the effect of 'Change in weaning management' at the end of the study period. In the latter case, defective scales that were not repaired adequately for several months caused multiple missing values in weight measurements. We decided to omit these observations instead of imputing the missing values, since these observations presented the last observations of the dataset ('embedded missing values').

On farm B, three batches were excluded from the analysis. These batches were marketed during the pre-Christmas period resulting in considerably lower market weights compared to other batches. Since pre-Christmas sales management does not have any biological meaning, these batches were not regarded as representative to answer the study question. Although a change in sales management during the pre-Christmas period may also have been present on the other two farms, differences in market weight compared to other batches were not as distinct as on farm B.

5.3.2 Data quality

Control of data quality is one of the key issues when conducting observational epidemiological studies, as the inferences drawn from a study are in large parts influenced by the quality of the data collected. Longitudinal data collection raises an additional problem regarding data quality, which is related to potential drifts over time not captured in the data, such as staff turnover and changes in equipment (e.g. degradation due to wear or upgrades due to new technology) (Arts et al. 2002).

The two major sources of data errors identified in the present data sets were missing values on farms A and C as well as unaccounted pigs on all farms. On farm A, three weight parameters included missing values in 3 to 10% of the observations and three feed parameters included missing values in 2 to 12% of the observations. No missing values occurred in 'WGT 3' and in 'Daily feed intake grower diet'. Both latter parameters were measured at the grower stage, whereas the feed and weight parameters with missing values were recorded at the weaner and finisher stage. Differences in the data recording equipment (e.g. scales, feed delivery systems) and staff motivation may have contributed to differences in missing values at individual production stages. On farm C, 'WGT 1', 'WGT 2' and 'Growth rate WGT 2 to WGT 3' were missing for 1.1%, 5.7% and 15.9% of the batches. Neither the missing value pattern on farm A (Figure 4.1.1) nor on farm C (Figure 4.3.1) indicated strong clustering of missing values. However, some clustering in time appeared to be present, so that we still assumed that missing values were missing at random (MAR) and not missing completely at random (MCAR).

Unaccounted pigs were a frequent and consistent data error found on all farms. It was more common that the recorded entry number was greater than the final move out number ('Surplus pigs') than vice versa ('Missing pigs'). The prevalence of batches with at least one surplus recorded pig was 72%, 95% and 42% on farms A, B and C, respectively. The median prevalence of surplus missing pigs within a batch was 1.3%, 3.5% and 1.4% on farms A, B and C, respectively. Surplus pigs are likely to be caused by counting too many pigs at batch entry or by unrecorded move out events, such as deaths, transfers and sales. The available data did not allow determining the cause of unaccounted pigs in the present study. Only on farm B, it could be assumed that most unaccounted pigs were due to unaccounted deaths and unaccounted transfers to hospital pens, since these events were not captured in the dataset. Furthermore, records on farm C did not reveal any weaner deaths over 10 subsequent study weeks (weeks 21 to 30) (Figure 4.3.6), which raises concerns about the truthfulness of these records.

Unaccounted pigs have also been identified as a problem in routinely collected production records in the study of Vaillancourt (1992). This study evaluated the internal consistency of routinely recorded pre-weaning mortality data from 109 US pig herds. The study reported that in 71% of the herds unaccounted pigs occurred in less than 15%

of litters. However, on the farm with the worst data quality, 77% of litters included unaccounted pigs. Surplus piglets occurred more frequently (8.0%) than missing pigs (4.7%). The lower prevalence of unaccounted pigs per litter compared to the prevalence per grower batch in our study may be due to the smaller observation unit (up to 20 piglets per litter compared to up to 160 pigs per batch). The fact that the prevalence of surplus recorded pigs was higher than the prevalence of missing pigs suggests that unrecorded deaths or move out events are more common recording errors than miscounting at entry to the grower herd.

None of the three datasets included a large number of obvious outliers. During intense data checks with original records, we were able to correct several outliers caused by transcription errors. Remaining suspected outliers were still present in several parameters. However, only outliers in feed measurements on farm A strongly deviated from the mean level of observed value, which might have been due to measurement errors. All other suspected outliers lied within a biologically plausible range, so that we did not exclude any outlier a priori.

Both, pro- and retrospective data were included in the analysis on farms A and B. An investigation of the data quality (missing values, outliers and unaccounted pigs) of retro- versus prospective data on these two farms was conducted in a separate study (data not yet published). We aimed to assess whether there had been a significant improvement in data quality in the prospective part of the dataset. This would suggest that results from the two merged data sources might have been biased by the study itself. On farm B, no difference between pro- and retrospective data was found. In contrast, on farm A, significant differences were detected in missing weight data and surplus recorded pigs. However, compared to prospective data, missing weight data (OR = 0.18, 95% CI: 0.12 – 0.25, $P < 0.001$) and surplus recorded pigs (OR = 0.59, 95% CI: 0.43 – 0.82, $P = 0.002$) were less likely to occur in the retrospective part of the dataset. The higher occurrence of missing values in 2004 was likely to be caused by the missing weight measurements between study weeks 141 and 163 due to defective scales. These batches were excluded from the current analysis. Due to a similar or higher data quality of the retrospective part of the dataset, we did not expect that merging retro- and prospective data biased our results.

5.3.3 Univariable descriptive analysis

It is well accepted that pork production is a chain of interdependent processes (Greenley 1997), each of which exhibits variation over time. The primary objective of this study was to determine factors influencing market weight. Furthermore, we also aimed to describe mean values as well as temporal fluctuations in measured predictor variables. This indicates what factors may have restricted farm productivity and profitability. In this section, we first evaluate differences in investigated parameters between the studied farms and compare them with reported literature values. Secondly, we briefly discuss potential variations due to seasonal effects considering that seasonal effects on predictor variables are purely descriptive without adjusting for confounding. Finally, we carefully suggest potential interrelationships between predictor variables in time on each individual farm.

<u>Comparison of mean values and temporal fluctuations of univariable parameters</u>

Outcome variable

Mean market live weight was lower on farm C (81.5 kg) compared to farms A (87.1 kg) and B (88.1 kg). One reason for that is that the packer company supplied by farm C favoured lighter pigs than the packer company supplied by farms A and B. A linear downward trend in 'Market weight' was observed on farms A ($P = 0.002$) and C ($P = 0.02$). On farm A, 'Days to market' (Figure 4.1.13) increased simultaneously resulting in a linear downward trend in growth rate from birth to market ($P < 0.001$). In contrast, on farm C, the linear downward trend in 'Market weight' was also apparent in 'Age at market' ($P = 0.009$) thus not resulting in a significant reduction in growth rate from birth to market ($P = 0.58$).

Farms B and C weighed pigs before marketing to increase the proportion of pigs sold at optimum weight and hence to reduce variation in market weights. This management practice appeared to be successful on farm B, where 'Market weight' showed low variability over time (CV = 2.5%). In contrast, on farm C, variability in 'Market weight' was similar (CV = 4.3%) to farm A (CV = 4.9%), which did not weigh pigs pre-marketing. Inconsistent 'Market weight' on farm C despite market selection appeared to be driven by the high variability in 'Weaning age', which was strongly associated with

‘Market weight’ (Table 4.3.3). Market selection may still have been effective in reducing within-batch variation. However, we could not assess this effect since variation between individual market weights could not be assessed on farm A.

Mean daily live weight growth rate from birth to market was 581 g/d, 634 g/d and 595 g/d on farms A, B and C, respectively. Hence, the maximum difference in growth rates was 53 g/d between farms. The observed growth rates compare favourable to reported lifetime growth rates on other commercial New Zealand pig farms. For instance, growth rates were 563 g/d in vaccinated pigs and 549 g/d in unvaccinated pigs in the study of Wongnarkpet (1999). In another vaccination study, pigs grew at a rate of 539 g/d and 575 g/d before and after vaccination, respectively (Lawton 2000). The same author compared carcass growth rates on a different New Zealand farm before and after a partial depopulation, which were converted to live weight growth rates (estimated killing out percentage: 75%) of 546 g/d and 619 g/d, respectively. Apart from the fact that no direct comparison can be drawn between the studied farms due to different management and health conditions, genetic improvement may also have contributed to the slightly higher growth rates observed in our more recent study. Another more recent study (Green et al. 2003) reported growth rates of 910 g/d during the grower/finisher phase (25 to 80 kg) on a commercial New Zealand pig farm. This compares high to grower/finisher growth rates of 782 g/d (farm A), 863 g/d (farm B), and 824 g/d (farm C) in our study. In conclusion, it can be said that observed growth rates in our study lied in the expected range of growth rates on well-managed commercial New Zealand pig farms.

Predictor variables

Farms differed in the parameters they collected (Table 3.4.1). In total, 25 (farm A), 19 (farm B) and 13 (farm C) predictor variables were assessed for their association with market weight. All farms counted pigs at entry and market, and weighed pigs at least three times throughout production. Breeding herd parameters were only collected on farms A and B, feed parameters only on farm A, and mortality data only on farms A and C. Investigated predictor variables included animal attributes, such as pig weights and pig mortality rates. Animal attributes reflect the animals’ response to environmental stressors (Martin 2004). Hence, animal attributes can be considered as indicator variables for external conditions (e.g. environment, diet), which were not monitored.

Breeding herd parameters

'Median parity of sows weaned' was similar across our studied farms (range in median values: 4.0 to 4.5). This parameter did not show any considerable long-term trend on any of the farms indicating a relatively stable herd age structure. However, this parameter showed more serial variation on farm C (IQR: 3.0 – 6.0) compared to farms A (IQR: 4.0 – 5.0) and B (IR: 3.5 – 5.0) (Figures not shown). This may be related to a more intense replacement policy on farm C, resulting in a greater variation of median sow parity between sow batches.

The median percentage of gilts per farrowing batch was similar across farms (farm A: 16.7%, farm B: 18.2%, farm C: 15.8%), whilst it was most variable on farm C. We only found one study to compare these values with, since most published data refer to the overall gilt inventory in the herd. King (1998) reported the median and the 90th percentile for the percentage of gilts farrowed on 482 US pig farms in 1995, which was 9.2% and 15.5%, respectively. The same study revealed evidence that the percentage of gilts in the breeding herd inventory is negatively associated with breeding herd efficiency. First, the number of non-productive days per breeding female decreases the more gilts are kept on the farm. Secondly, gilts are less productive than multiparous sows in that both, their farrowing performance (Koketsu 2005) and the growth performance of their piglets (Daza et al. 1999b) are lower. However, on the other hand, a large enough stream of replacement gilts is necessary to fill breeding deficits of varying size (Greenley 1997). Our studied farms could potentially explore opportunities to reduce the percentage of gilts in their farrowing batches to enhance their breeding efficiency and to reduce variation in grower herd performance.

A median number of ten pigs was weaned per litter on all farms. Two studies reported similar values for high performing US herds, which weaned 9.4 (Stein et al. 1990) and 9.5 piglets per litter (Koketsu 2000). This parameter was more variable on farm C similar to 'Median parity of sows weaned' and 'Percentage of gilts farrowed'. On this farm, a progressive replacement of unimproved genotype sows with modern genotype sows took place up to approximately study week 41 (Figure 4.3.2). This may explain the greater variability in breeding herd data. However, available descriptive values for breeding herd data were produced after the replacement was well proceeded and all sows were entered into PigLITTER®. Therefore, other factors may have contributed to the greater variation in herd age structure and weaning numbers.

Observed median levels of pre-weaning mortality (farm A: 10.8%, farm B: 10.3%, farm C: 8.5%) were slightly lower than reported values from New Zealand and US pig farms. For instance, mean pre-weaning mortality rate was 13.2% (SE ± 0.13%) on 18 commercial New Zealand farms over a ten-year period (1980 to 1989) (Skorupski et al. 1995). Similarly, production data from 54 US pig farms (years 1985 – 1986) (Stein et al. 1990) and from 593 US pig farms (year 1995) (King et al. 1998) revealed pre-weaning mortality rates of 14.5% (SD ± 4.6%) and 13.0% (SD ± 4.1 d), respectively. Low pre-weaning mortality rates on the studied farms indicate good farrowing house management.

Dewey (2000) assessed variation in weaning age on eight Ontario farms resulting in coefficient of variations (CV) ranging from 17 to 37%. Similarly, CV in weaning age was 17.4% on 54 US pig farms (Stein et al. 1990) and 21.8% on 591 US pig farms (King et al. 1998). Observed values for this parameter in our study (farm A: 7.6%, farm B: 8.2%, farm C: 11.8%) lied below this range. This indicates a good mating and farrowing management so that batches of sows farrow within a short period.

Entry parameters

On farms A and B, only part of the batch originated from the farrowing rooms, whilst the remainder of the batch came from the special rearing location (SRL). A SRL has several advantages. First, rearing lightweight pigs in a specialized environment (higher temperature, specialized diet) improves their growth performance and their likelihood of survival (Snelson 2000). Secondly, removing light pigs from the weaning batch reduces within-batch variation at market (Sornsen 1998). Thirdly, operating a SRL allows to balance fluctuations in weaning numbers with pigs from the SRL. On the other hand, a SRL is generally operated on a continuous flow system so that piglets from different weaning batches are mixed together. This presents a considerable health risk for the pigs in the SRL as well as for the batches these pigs are mixed with later on. Furthermore, the production cost of operating a SRL is not necessarily justified by the performance benefits (Sornsen 1998). In terms of performance monitoring, it is hard to say how pigs from the SRL perform compared to directly weaned pigs. Especially if the exact age of pigs from the SRL is not known, variations in ‘Percentage of pigs weaned directly’ present a considerable source of bias.

Farms A, B and C weaned piglets at approximately 34, 28, and 26 days of age. In addition to weaning pigs at the youngest age, variability in weaning age between grower batches was highest on farm C (CV = 14.6%) compared to farms A (CV = 2.7%) and B (CV = 6.0%). As a result, six batches (study weeks 56, 79, 80, 81, 89 and 90) were weaned below 21 days of age. In New Zealand, the Code of Animal Welfare No. 13, released from MAF in 1999, proscribes: “Weaning below four weeks of age should take place only when there is a very efficient management system and piglets should not be weaned under 5.5 kg body weight unless there are exceptional circumstances.” In other major pig producing countries, piglets are weaned at three to four weeks of age. Weaning at less than three weeks of age when maternal immunity is still high in combination with off-site weaning is a management strategy called segregated-early weaning. Despite proven health benefits in segregated-early weaned pigs, it is scarcely performed in commercial production due to high staff and hygiene requirements for milk feeding of these piglets. Due to strong expected associations between weaning age and post-weaning growth performance, we recommend reducing variability in weaning age to a minimum.

Our studied farms varied in their production capacity resulting in median weekly numbers of 160, 107, 78 pigs entering the grower herd on farms A, B and C, respectively. Variability in ‘Entry numbers’ was similar on farms B (CV = 9.5%) and C (CV = 9.9%) compared with farm A (CV = 2.6%). Variations in pig flow present a considerable opportunity loss, since the system capacity is not used adequately. Farms A and B operated a special rearing location (SRL), which enabled the farms to balance their entry numbers. However, the CV in ‘Entry numbers’ was of similar magnitude on farm B as on farm C, which did not use a special rearing location. This may be due to the fact that farm B used pens in a separate shed (shed E) to accommodate surplus pigs of intermittent batches resulting in different housing capacities between batches.

Mortality data

Mortality data were only recorded on farms A and C. Mortality was highest at the weaner stage on both, farm A (1.1%) and farm C (0.9%), whilst both, grower (farm A: 0.2%, farm C: 0.4%) and finisher mortality rates (farm A: 0.6%, farm C: 0.2%) were low. Recorded mortalities compare low to reported values from the US (Losinger et al. 1998b). However, the occurrence of unaccounted pigs and periods with no recorded pig deaths may indicate unrecorded deaths and hence underestimation of mortality rates on both farms.

Sample weights

The trellis plots illustrate that growth curves were more variable on farm A (Figure 4.1.6) compared to farms B (Figure 4.2.6) and C (Figure 4.3.7). This may be caused because either true between-batch variation was greater or sample weight measurements were less accurate on farm A. Whilst greater between-batch variation presents a considerable opportunity cost to the farm (Deen 1998; Deen 1999), reduced accuracy in sample weights would present a data quality problem and hence affect the accuracy of the model. In order to determine, which of the two reasons were applicable on farm A, one has to consider the issue of sample size.

The proportion of pens sampled affects the accuracy of sample weight (Schauer et al. 2005a). For two different datasets (grower and finisher weights), the association between sample weights at different sample sizes and 'true' batch weight was assessed using the R-squared value. Results from both datasets showed that, after random selection of pens, the accuracy of sample weights increases in a logarithmic manner with increasing sample size. Farm B weighed the entire batch at all stages, whereas farm C weighed 27 to 38% of the batch throughout production and 100% of the batch at marketing. In contrast, the proportion of the batch weighed on farm A was 100% at weaning, 25 % at the grower stage, and 10% at the finisher stage. Since weight variation on farm A increased the later the sample weights were taken, sample size may have introduced bias to the sample weight measurements causing at least some of the variation observed in the trellis plots.

Under non-limiting conditions, the growth curve from birth to maturity is of sigmoid shape with a self-accelerating part up to the point of inflection where growth rate is maximal. Thereafter, growth is self-decelerating reaching the plateau in an asymptotic manner. Assuming a mature body weight of 220 kg, the Gompertz function predicts the point of inflection (0.368 times the mature weight) to be at 81 kg body weight. Since pigs in New Zealand are marketed at approximately 90 kg live weight, most of their growing period lies within the self-accelerating part of the growth curve.

Growth curves on farms A and B tended to flatten during the finisher stage, whilst on farm C growth tended to increase up to marketing. Differences in feed availability may partly explain these differences, since farm C was the only farm feeding finisher pigs ad-libitum in contrast to restricted feeding of finisher pigs on farms A and B.

Feed data

Feed data were only recorded on farm A. Mean values of 0.156 kg/d (day 0 – 22 post-weaning), 0.722 kg/d (day 23 – 47 post-weaning), 1.851 kg/d (day 48 – 61 post-weaning) and 2.189 kg/d (from day 62 post-weaning until market) for the four subsequent diets lie in the expected range of daily feed intake. Several outliers were present in each of the four time series for the feed intake parameters possibly indicating measurement error.

<u>Seasonal effects</u>

Seasonal effects were consistently detected in weight parameters on farms A and B and in all but one feed intake parameter on farm A. The effect of season on weight gain and feed intake will be discussed concurrently, as they are strongly interrelated. The lack of a seasonal effect on weight measurements on farm C may be related to fluctuations in weaning age. Additionally, the study period on this farm did not cover two full years resulting in lower sample sizes in autumn (n = 13) compared to other seasons (n = 25) (Figure 4.3.5). The effect of season on other parameters than weight and feed intake was inconsistent and will not be further addressed.

Ambient temperature is clearly one factor explaining seasonal variation in feed intake and weight gain. The animal's heat production is regulated by muscle activity (shivering, physical activity), feed consumption and metabolic changes. For instance, it was shown that physical activity is lowered in hot temperatures (Brown-Brandl et al. 2000; Kerr et al. 2003) and increased in cold temperature (Quiniou et al. 2001). However, regulation of feed intake is an important mean of thermoregulation since the activity of chewing and subsequent organ work during ingestion produce heat. A reduction in feed intake in hot temperatures and an increase in feed intake in cold temperatures is well documented (Rinaldo et al. 1991; Le Dividich, J., Noblet, J., Herpin, P., van Milgen, J., Quiniou, N. 1998; Quiniou et al. 2000; Le Bellego et al. 2002). Consequently, in hot temperatures, growth rate is reduced as a direct consequence of the reduction in feed intake, whereas feed efficiency is mostly found to be unaffected (Rinaldo et al. 1991; Le Bellego et al. 2002). A different situation occurs in cold temperatures. If feed intake can be sufficiently increased to compensate heat loss to the environment, growth rate will be unaffected. However, due to the energetic cost of increased heat production, feed efficiency is decreased. In contrast, growth rate will be reduced if gut capacity limits a sufficient increase in feed intake to compensate heat loss.

Additionally, there is an interactive effect between the response in feed intake to changes in ambient temperature and the pig's body weight (Quiniou et al. 2000). On the one hand, in high temperatures larger pigs reduce their feed intake to a stronger extent than smaller pigs. On the other hand, in cold temperatures smaller pigs are less capable of increasing their feed intake due to a limited gut capacity.

Both, hot and cold temperatures imply a direct loss to production, either due to increased time to reach market weight or due to a reduction in feed efficiency. Hence, strategies to reduce the impact of adverse temperatures are beneficial. At high temperatures, increasing the ventilation rate, reducing stocking density and providing sources of water (sprinklers, higher water pressure of drinkers) reduce the effect of heat. Furthermore, dietary manipulations are efficient in enhancing performance levels at low feed intakes. This can either be done by increasing the energy level at similar protein levels in the diet or by reducing the protein level only (Le Dividich, J. et al. 1987; Le Bellego et al. 2002). For instance, Le Bellego (2002) showed that reducing dietary crude protein by 4% whilst maintaining an optimum ratio of essential amino acids and energy reduced the negative effect of high temperatures (29°C) on feed intake without affecting growth or carcass composition. In cold temperatures, any intervention, which keeps the pigs warm, will prevent further increase in voluntary feed intake, whereas dietary manipulations have been shown to be ineffective (Le Dividich 1987).

Other factors causing seasonal variation in feed intake and growth are disease levels (particularly enzootic pneumonia) (Scheidt, A. B. et al. 1992; Maes et al. 2001a), variations in feed quality (e.g. mycotoxins, nutrient content) (Lauren et al. 1996; Kim, J.

C. et al. 2003) and air quality (Duchaine et al. 2000; Asmar et al. 2001). Since it is impossible to control all these seasonal factors, season is an important confounder to consider in the analysis.

<u>Special features on individual farms</u>

Farm A

As noted above, ‘Growth rate from birth to market’ decreased linearly over time due to the combined decline in ‘Carcass weight’ (Figure 4.1.12) and increase in ‘Days to market’ (Figure 4.1.13). A linear downward trend was also apparent in sample weight 2 (Figure 4.1.8), sample weight 3 (Figure 4.1.9) and ‘Growth rate from sample weight 3 to 5’ (Figure 4.1.10). This suggests that the performance decline was driven by factors occurring before sample weight 2-measurements (30 days post-weaning).

It could be hypothesized that the substantial reduction in the use of feed antibiotics in 2001 may have decreased performance. However, this would have presumably resulted in a level shift in performance rather than a long-term reduction. Unfortunately, the study period did not cover the period before the reduction in feed antibiotics, so that the effect could not be evaluated.

It is likely that pigs entering batches from the special rearing location (SRL) caused part of this ‘apparent’ performance decline since the age of these pigs was not known. First, the ‘Proportion of piglets weaned directly’ showed a significant level shift over the years with a median level of 56%, 93% and 76% in 2001, 2002 and 2003, respectively. Additionally, move in and move out weights of pigs entering and leaving the SRL were significantly lower in 2002 and 2003 than in 2001 (Table 4.1.2). This strongly suggests that the initial condition of pigs entering the SRL as well as the length of time these piglets stayed in the SRL varied over time. If piglets stayed longer in the SRL in 2001 whilst contributing approximately half of the piglet numbers entering a batch, then the actual entry age of these batches would be proportionally higher than the entry age of batches in 2002 and 2003. As a result, batches in 2001 may have been sold after a shorter time post-weaning, whilst possibly being of a similar age. This indicates clearly that the variation in ‘Percentage of pigs weaned directly’ presents a considerable source of bias. The effect of piglets entering from the SRL may vary depending on their entry weights and length of time they remain in the SRL. Hence, we strongly recommend recording the age and entry weight of pigs from different sources to accurately interpret performance changes.

Additionally, ‘Weaning weight’ appeared to be associated with the observed performance decline. ‘Weaning weight’ and overall entry weight (‘Sample weight 1’) were highly correlated ($r = 0.92$, $P < 0.001$), and both parameters showed a similar time pattern. Despite the high consistency of weaning age (Median: 34 days, IQR: 33 to 34 days), ‘Sample weight 1’ (Figure 4.1.7) showed high variability between study week 33 and 69 and continued to decline until approximately the end of 2002. This was associated with a drop in ‘Entry numbers’ (Figure 4.1.3) ($r = 0.36$, $P < 0.001$), a high ‘Proportion of piglets weaned directly’ ($r = -0.39$, $P < 0.001$) and an increase in ‘Weaner mortality rate’ (Figure 4.1.5) ($r = -0.23$, $P = 0.007$). We conclude that the observed decline in performance may have partly been apparent due to fluctuations in the pig population temporarily housed in the SRL. However, in addition, a problem in the breeding herd appeared to be present in 2002 resulting in lower weaning weights and lower growth rates at subsequent production stages.

The number of pigs entering a batch was consistent in 2001 and 2003, whereas entry numbers highly fluctuated in 2002 (study weeks 56 to 102) (Figure 4.1.3). Fluctuations in entry numbers present a substantial opportunity cost, since the profit on a pig farm is driven by margin over feed cost as well as overall throughput. For instance, in 2002 (missing weaning event imputed with 156 pigs), 375 less pigs were sold than in 2001 (n = 8194). Based on a mean carcass weight of 64.9 kg and a mean price per kg of NZ \$ 3.3, the farm received approximately NZ \$ 80,300 less revenue than in the previous year. We strongly recommend monitoring and controlling entry numbers to assure a constant throughput of pigs. Mating management, farrowing rate and number of pigs weaned per litter would be the preceding measures to control variability in ‘Entry numbers’.

Farm B

‘Market weight’ (Figure 4.2.9) and ‘Days to market’ (Figure 4.2.10) were relatively stable throughout the study period. However, a slight decrease in ‘Market weight’ with a simultaneous increase in ‘Days to market’ was apparent in 2003. The reduction in

‘Sample weight 1’ and ’Growth rate WGT 1 to WGT 2’ over a similar period indicated this performance decline. Changes in other parameters over this period included an increase in ‘Percentage of gilts farrowed’ and ‘Coefficient of variation in weaning age’ as well as a reduction in ‘Median parity of sows weaned’ and ‘Entry numbers’. It is possible that the higher ‘Percentage of gilts farrowed’ resulted in an increase in ‘Coefficient of variation in weaning age’ since the oestrus of gilts is more difficult to synchronize than the oestrus of multiparous sows (Kirkwood 1997). This effect in addition to the known disadvantages of piglets from gilt litters may have contributed to the reduced growth performance.

‘Entry numbers’ declined in 2003, increased over the first three months in 2004 and declined again thereafter. The latter decline may have been associated with a reduction in ‘Median number of piglets weaned per litter’ over the last few study weeks. We recommend monitoring breeding herd parameters to detect deficiencies in breeding herd performance at an early stage. This will minimize production losses due to variations in pig throughput.

Farm C

‘Market weight’ (Figure 4.3.11) dropped considerably over the first few study weeks. The sudden drop in ‘Market weight’ of batches weaned in study weeks 12 to 15 was related to sale dates during the pre-Christmas period. However, in contrast to farm B, we did not exclude these batches from the analysis, as there was no such difference in sales weights of batches sold during the pre-Christmas period in 2004 (study weeks 65 to 67). Generally, ‘Days to market’ (Figure 4.3.12) was more stable than ‘Market weight’. This indicates that ‘Days to market’ was the driving factor for making sales decisions, which was most likely caused by limiting housing facilities at the finisher stage.

Overall, ’Market weight’ showed a significant downward trend ($P = 0.02$), which appeared to be predominantly associated with decreasing market weights throughout 2004. This appeared to be associated with a decline in ‘Weaning age’ (Figure 4.3.4) over a similar period. This was supported by the fact that fluctuations in ‘Weaning age’ corresponded closely with fluctuations in ‘Market weight’ ($r = 0.60$, $P < 0.001$) as well as with ‘Sample weight 1’ ($r = 0.70$, $P < 0.001$) and ‘Sample weight 2’ ($r = 0.75$, $P <$

0.001). The strong effect of weaning age on subsequent weight measurements was expected, since pigs weaned at a younger age will be younger and presumably lighter at sample weight measurements taken at a fixed day post-weaning.

Similar to 'Weaning age', 'Entry numbers' (Figure 4.3.3) showed high variability over time. The observed increase in 'Entry numbers' at the end of 2004 is possibly related to the expansion of the breeding herd. However, simultaneously, the variability in entry numbers increased from mid-2004 (study week 51 onwards), in contrast to a relatively stable period between study weeks 15 and 50. Variability in pig flow presents a high opportunity cost. Given an optimum pig capacity of the farm, a shortage in pig numbers means that housing facilities are not used to their optimum, whereas an excess in pig numbers results in overcrowding and has adverse effects on growth performance. High variability in both, 'Entry numbers' and 'Weaning age', indicates an inconsistent breeding herd output. Although breeding herd parameters were not included in the model building since they were only assumed to be complete over the last 47 study weeks (Figure 4.3.2), these parameters were more variable than on farms A and B (see above).

In summary, several parameters showed greater variability on farm C than on farms A and B. The producer had purchased the farm as an old-type pig farm (unimproved genotype, old buildings) only eight months before study start. Hence, the entire system was undergoing a process of change throughout the study. Changes in diets, housing facilities and sow breeding stock throughout the study period as well as a less established routine in herd management may have caused some of the observed variation. However, the collected production records will be of great value when assessing the ongoing improvement of the production system.

5.3.4 Univariable time series analysis

The Autocorrelation Function (ACF) and the Partial Autocorrelation Function (PACF) indicate positive autocorrelation of the original series of market weights at lag 1 on farms B (Figure 4.2.11) and C (Figure 4.3.13) and at lags 1 and 2 on farm A (Figure 4.1.19). Due to the presence of a deterministic trend in 'Market weight', autocorrelation estimates were compared between the raw series and the detrended series on farms A (Figure 4.1.19) and C (Figure 4.3.14). For both farms, autocorrelation estimates of the raw series were consistently higher than of the detrended series. This is in agreement with the study of Yue (2003) who suggested that autocorrelation estimates for a time series with underlying trend will overestimate positive autocorrelation and underestimate negative autocorrelation. However, the identification of the underlying time series process was the same in the raw and the detrended series.

When fitting a univariable autoregressive model to the outcome variable (no inclusion of predictor variables), estimated first-order autoregressive parameters were -0.50, -0.61 and -0.72 on farms A, B and C, respectively. These models enabled to forecast future parameters with an accuracy of 40.3% (farm A), 36.2% (farm B) and 49.8% (farm C). However, remaining autocorrelation at several lags was present on all farms suggesting that other factors were also influencing ‘Market weight’ on each farm. The fact that autocorrelation remained at one or more lags between lags 12 and 15 on all farms suggests a seasonal influence. Hence, if farms were to use univariable autoregressive methods to predict fluctuations in market weight, they will need to adjust for seasonal fluctuations. The reader is referred to Brockwell (2002) and Shumway (2006) for a detailed discussion of seasonal adjustment.

5.3.5 Multivariable regression analysis with autoregressive error correction

5.3.5.1 Farm A

We first tried to fit a first-order autoregressive model, although the ACF and PACF indicated a second-order autoregressive process, However, residuals from the final first-order autoregressive model showed remaining autocorrelation at lag 2 ($P = 0.009$). Hence, we then developed an autoregressive model including a first- and second-order autoregressive term.

The final model (Table 4.1.4) included six main effects (DF = 6), two interaction effects (DF = 2) and two autoregressive parameters (DF = 2). Using 7.2% of the valid observations as degrees of freedom raises no concern of overfitting.

The model explained 80.2% of the variance in the observed values of ‘Carcass weight’. In comparison, the structural part alone produced a R^2-value of 69.1%. It is a particular advantage for the producer that all parameters of the model could be obtained by 76 days post-weaning apart from ‘Days to market’. Being able to forecast ‘Carcass weight’ of immediate future batches a month prior to marketing with 80.2% confidence, offers a strong opportunity to improve marketing returns.

‘Growth rate WGT 3 to WGT 5’ had a positive effect on ‘Carcass weight’. However, the estimated effect on ‘Carcass weight’ is small (+0.0031 kg per g increase). This predicted increase in carcass weight converts to a predicted increase in live weight of 0.0041 kg using a 75% killing out percentage. This presents only 15% of the 28 g live weight gain per gram increase in growth rate over a 28-day period. It is likely that the effect of ‘Growth rate WGT 3 to WGT 5’ is in part accounted for by the other parameters in the model thus only adjusting for minor deviances. Despite the marginal significance of ‘Growth rate WGT 3 to WGT 5’ ($P = 0.049$), this parameter significantly improved the model fit as assessed by the -2 Log Likelihood ratio test ($P = 0.037$).

Batches housed in finisher shed B were 0.69 kg heavier at market than batches housed in shed A, although both sheds were of equal design. However, differences in the functionality of equipment such as the ventilation or feeding system may have contributed to this effect.

Estimated coefficients of ‘Study week’, ‘Entry weight weaner stage’ (WGT 1), ‘Entry weight finisher stage’ (WGT 3) and ‘Days to market’ need to be interpreted whilst considering their interaction terms. The significant interaction between WGT 1 and ‘Study week’ indicates a time-varying effect of WGT 1. The model predicts that the increase in ‘Market weight’ by 2.10 kg per kg increase in WGT 1 at study week 0 decreases by 0.012 kg per week. Considering the effect of ‘Study week’ alone indicates that ‘Market weight’ decreases by 0.024 kg per week (1.25 kg per year) after accounting for both, the main and interaction effect using the mean of WGT 1 (9.3 kg). The decrease predicted by the regression model corresponds closely with the trend line estimate of -0.021 kg for the raw data. This suggests that the selected predictor variables explained only a small portion of the downward trend in ‘Market weight’. Hence, it appears that other unmeasured parameters up to 76 days post-weaning or factors occurring after 76 days post-weaning may have explained the observed downward trend in ‘Market weight’.

The positive interaction between WGT 3 and 'Days to market' suggests that 'Market weight' of heavy pigs entering the finisher stage will be increased to a greater extent per day increase in 'Days to market' than 'Market weight' of light finisher pigs. This is in accordance with results of Dunshea (2003), who showed that pigs being heavy-for-age at weaning increased their weight advantage over time. The initial weight advantage of 3 to 4 kg at weaning increased to 13 kg at market compared to lighter pigs of the same age. Similarly, growth curve analysis has shown that heavy-for-age pigs increase their weight at a greater rate than lighter pigs (Schinckel et al. 2003). This is most likely due to a higher rank in the dominance hierarchy (Rasmussen et al. 2006) and to a greater feed intake capacity of larger animals (Whittemore 1993). The effect of 'Days to market' alone given a mean of WGT 3 (37.1 kg) predicts that each unit increase in 'Days to market' results in a 0.523 kg greater 'Market weight'. It is tempting to interpret this value as the growth rate during the finisher stage. However, the calculated value will be affected by the effect of other predictors and thus cannot be interpreted independently. In comparison, the mean descriptive value for growth rate from WGT 5 (76 days post-weaning) to 'Market weight' was 741 g/d, which is 218 g/d higher than the isolated effect estimate of the regression model.

5.3.5.2 Farm B

A combination of five main effects (n = 8), two interaction effects (n = 6) and one autoregressive term (n = 1) best described the observed values of 'Market weight' on farm B (Table 4.2.4). Fifteen degrees of freedom present 12% of the total sample size (n = 124). Hence, overfitting of parameters presented no major concern.

The structural part of the model explained 60.9% of the variance in 'Market weight'. Using the information of past residuals enables prediction of observed and forecasting of immediate future values with a probability of 73.3%. All parameters could be collected by 78 days post-weaning apart from 'Days to market', which is kept as a changeable input parameter. Therefore, the producer can estimate 'Market weight' approximately a month prior to marketing.

'Entry weight grower stage' (WGT 1), 'Growth rate WGT 1 to WGT 2', 'Days to market', 'Season of weaning' and 'Finisher shed type' were identified as significant risk factors. Both interaction terms included 'Season' with spring as the reference category.

Hence, we first draw inferences for batches weaned in spring only, since then the interaction effects do not affect predictions of 'Market weight'.

'Entry weight grower stage' (WGT 1) and 'Growth rate WGT 1 to WGT 2' may be regarded as indicator variables for batch performance at the sucker/weaner and grower stage, respectively. Both parameters had a positive effect on 'Market weight'. This was expected since heavier pigs grow generally faster than lighter pigs, subsequently becoming heavier at an older age (Dunshea et al. 2003; Schinckel et al. 2003).

Furthermore, a positive effect of 'Days to market' on 'Market weight' was expected since growth presumes that body weight increases with time. An increase in 'Market weight' by 0.96 kg for every day increase in days to market gives an indication of the daily growth rate during the finisher stage for batches weaned in spring. This value is similar to the mean descriptive values of the finisher growth rate (0.811 kg/d) from 78 days post-weaning to market. However, the model estimate for the effect of 'Days to market' may have been inflated by the influence of other variables.

Shed effect is a common confounder in observational studies. Batches housed in shed type B and C were 1.04 kg and 0.66 kg heavier at market than batches housed in shed type A. Finisher sheds varied in pen design, ventilation, group size and feeder space. Thus, it is hard to determine, what may have caused the observed performance differences between sheds. One possible explanation for the advantage of shed type B and C may be the better ventilation found in sheds B and C, which may further be related to lower pneumonia levels for batches housed in these sheds.

Significant interactions were found between season and 'Days to market' as well as season and WGT 1. The interaction effects indicated that 'Days to market' and WGT 1 had a greater effect on 'Market weight' for batches weaned in spring than for batches weaned in other seasons. After a post-weaning growth period of approximately three months, batches weaned in spring will be marketed in summer. Lower pneumonia levels in finisher pigs marketed in summer (Scheidt, A. B. et al. 1992) and favourable temperatures in spring and summer may explain the improved growth performance of batches weaned in spring.

5.3.5.3 Farm C

A combination of six main effects (n = 8), one interaction effects (n = 3) and one autoregressive term (n = 1) best described the observed values of 'Market weight' on farm C (Table 4.3.4). Twelve degrees of freedom present 13.6% of the total sample size (n = 88). This does not indicate overfitting of model parameters.

The model enables to predict observed and forecast immediate future values with 75.0% accuracy. The structural part of the model alone accounted for 57.8% of the variation in the data. All parameters apart from 'Days to market' could be obtained by 75 days post-weaning, so that 'Market weight' can be determined with 75% probability one month prior to marketing.

We tried to capture ongoing management changes by investigating the effect of diet change and the estimated proportion of piglets weaned from modern genotype sows. However, none of these parameters reached statistical significance.

The model predicts that 'Market weight' decreases with increasing entry numbers. It is generally accepted that increasing group size reduces growth performance. Additionally, increasing group size reduces floor space (Turner et al. 2000; Hyun et al. 2002; Hamilton et al. 2003), feeder space (Georgsson et al. 2001; Turner et al. 2002) as well as the available air space per pig (Buddle et al. 1997; Maes et al. 2000; Stark 2000). All these factors may contribute to the predicted reduction in growth rate for every additional pig entering a batch.

'Sample weight 2' (WGT 2), 'Growth rate WGT 2 to WGT 3' and 'Days to market' had a positive effect on 'Market weight'. The first two variables are basically growth indicators, since it is accepted that body weight is positively associated with body weight at any later stage (Dunshea et al. 2003; Schinckel et al. 2003). Furthermore, growth implies that body weight increases with age thus explaining the positive effect of 'Days to market'.

'Weaning age' and its interaction with season achieved significance in the model. The model predicts that in other seasons than spring, 'Weaning age' has a positive effect on 'Market weight' (Figure 4.3.15). In contrast, for batches weaned in spring, the model predicts a reduction in 'Market weight' by 50 g for every day increase in weaning age.

This is in contrast with literature findings, which suggest that weaning age (Dunshea et al. 2003; Main et al. 2004) and weaning weight (Bruininx et al. 2001; Wolter et al. 2001; Dunshea et al. 2003) are the greatest determinants of immediate post-weaning and subsequent lifetime performance. This has been related to a greater development in the gastrointestinal tract resulting in greater feed intake (Dunshea et al. 2002; Pluske et al. 2003), better feed digestibility (Pluske et al. 2003) and lower likelihood of gastrointestinal problems (Skirrow et al. 1997; Madec et al. 1998). However, the predicted negative effect of weaning age is small (-50 g/day increase). Furthermore, 'Weaning age' in spring covers a smaller range (Figure 4.3.5) than 'Weaning age' in other months. Therefore, this apparent controversial effect does not present a major concern.

5.3.5.4 Overall

The models are relatively simple resulting in four to six variables that need to be monitored. As expected, weight measurements were strong predictors for 'Market weight'. These parameters present animal attributes reflecting the animal's response to its environment (such as feed, disease, and housing). In contrast, 'Weaning age' and 'Days to market' are predominantly management decisions, both of which are known to be positively associated with live weight. The categorical variables 'Finisher shed' (farms A and B) and 'Season' (farms B and C) are typical confounders in epidemiologic studies. Both these variables are easily obtainable thus not requiring much effort for data collection.

The structural part of the AR-model predicted 'Market weight' with greater accuracy on farm A (R^2 = 0.691) than on farms B (R^2 = 0.609) and C (R^2 = 0.578). One possible explanation for the greater accuracy may be that predictor variables were less variable on farm A than on the other farms (see section 5.3.3). Furthermore, the model accuracy on farm C may have been affected by the fact that the farm management has undergone several changes throughout the study period, which could not be captured in the model. However, on the other hand, farm A was the only farm with a significant linear trend ('Study week') included in the model. A linear downward trend as predictor variable will be restrictive when forecasting performance of future batches as it assumes that performance keeps declining. Therefore, if the producer aims to forecast performance of future batches, model parameters will need to be re-evaluated by either including a more flexible trend line estimate or by including information from predictor variables other than ‘Study week’. We tried to develop a multivariable model without including a trend effect. However, a deterministic trend remained in the model residuals hence violating the assumption of independency (P = 0.03).

Our analysis has two limitations. First, since the batch is the unit of interest and all farms applied split marketing, predicted mean ‘Market weight’ is only valid if a batch is marketed in a similar manner as the source population. Marketing patterns of each farm were reasonably consistent over time (data not shown). An alternative approach would have been to include an indicator variable to describe changes in marketing patterns over time in the model. However, it would have been difficult to describe a distribution by a single parameter. Alternatively, we would have had to choose the individual animal as the unit of interest. However, the data structure did not allow for this approach and the individual animal is not the unit of interest on commercial farms. Hence, model outputs need to be applied by attempting to market animals in a similar distribution as in the source population.

The second limitation is that individual parameters cannot be changed arbitrarily. For instance, ‘Days to market’ cannot be manipulated over a wide range without affecting the validity of the other parameter estimates. We recommend obtaining a rough forecast of ‘Days to market’ by using a univariable time series model. This approximate estimate can then be used to manipulate ‘Days to market’ over a narrow range to obtain the desired market weight. Alternatively, ‘Days to market’ and ‘Market weight’ could have both been chosen as outcome variables (Shumway et al. 2006). However, this would result in a more complex statistical analysis.

The magnitude of the first-order autoregressive term (AR1: -0.50, -0.61 and -0.72 on farms A, B and C) derived from the univariable time series model was markedly diminished when the effect of other predictor variables was taken into account (AR1: -0.19, -0.41 and -0.39 on farms A, B and C). In contrast, the magnitude of the second-order autoregressive parameter on farm A did not change considerably. One disadvantage of the autoregressive model is that the autoregressive parameters cannot be interpreted and contain little useful information (Harvey 1997). They are simply a mathematical representation of the autocorrelation observed in the series. However, despite this drawback, autoregressive modelling has been successfully applied in many disciplines.

5.3.6 Comparison of ordinary least squares (OLS) and autoregressive (AR) model

We estimated parameters predicting ‘Market weight’ using two different estimation methods: an autoregressive model (AR) using maximum likelihood methods and a simple linear regression model using ordinary least squares (OLS) methods.

The parameters selected during univariable screening differed on farms A and B, whereas they were the same on farm C. Parameter estimates derived from the univariable model were generally larger in the OLS-model. Only parameter estimates for ‘Study week’ on farms A and C as well as ‘Days to market’ and ‘Percentage of gilts farrowed’ on farm A were smaller in the OLS-model than in the AR-model. Similarly, standard errors of most parameter estimates derived from the univariable model were larger in the OLS-model apart from season (farms A and C), ‘Days to market’ (farms A and B) and ‘Sample weight 1’ (farm A). It may be hypothesized that the effect of predictor variables is more emphasized, but less accurate (higher variability) in the OLS-model, which does not explain variations over time using autoregressive parameters.

Residuals from the multivariable OLS-models showed no residual autocorrelation on farm A (Table 4.1.7). Compared to the AR-model, the OLS-model on farm A included two more main effects (DF = 2) and one more interaction effect (DF = 1), but no autoregressive parameters (DF = -2). The R-squared value produced by the OLS-model (R^2 = 0.810) was higher than both, the regression (R^2 = 0.691) and the total R-squared value (R^2 = 0.802) of the AR-model. When comparing included parameters and their parameter estimates, it is apparent that the effect of study week is more pronounced in the OLS-model and is included in one more interaction term compared to the AR-model. Hence, the interactive effect of study week with two predictor variables appears to capture the time-depending effects sufficiently resulting in residuals, which are not autocorrelated. After selecting the same parameters for the OLS-model as in the AR-model (‘reduced model’), residuals of the OLS-model were autocorrelated at lags 1 to 3. Furthermore, the R-squared value was lower than the total R-squared value of the AR-model. Hence, we concluded that the AR-model presented a better description of the data than the OLS-model.

On farms B and C, residuals of the final OLS-model showed remaining positive autocorrelation at lag 1 on farms B (Table 4.2.7) and C (Table 4.3.6) as well as at higher lags (farm B). Therefore, the OLS-model on farms B and C was biased as the model assumption of independent residuals is violated. The fact that autocorrelation is not explained by the predictors, suggests that the data is confounded by other time-varying risk factors, which are not captured in the dataset.

5.4 Factors causing bias

5.4.1 Study design

This study was designed as an observational study using routinely collected data from commercial farms. Therefore, the investigator had no direct control over data collection or possible confounders. Consequently, biases due to data quality problems, unmeasured confounding and correlation among predictor variables may have been present in our data. Accordingly, results from our study only allow to make inferences about associations under conditions found on the studied farms.

Another potential source of bias presents the fact that the study included both, retro- and prospective data, on farms A and B. The awareness of the pig producer and farm staff that data are to be used for study purposes, may have increased their efforts to record data accurately. Hence, the commencement of the study itself may have caused bias ('contamination bias'). However, results from a separate, not yet published analysis showed that there were no differences in data quality on farm B, whilst data quality on farm A was better in the retrospective part of the dataset than in the prospective part. Therefore, we did not consider inclusion of both, pro- and retrospective data, as a major concern.

Another problem may have arisen from prospective data collection as prospective studies are known to be more prone to qualitative interaction (Ducrot et al. 1998). Qualitative interaction occurs if the observation of a phenomenon might produce a change in the observed phenomenon. For instance, qualitative interaction is present, if the pig producer reacts to observed performance patterns throughout the study by applying some change to the farm management. Although especially towards the end of the study, farms received some feedback on marketing and performance efficiency in return for their effort in data collection, this did not appear to result in immediate management changes. The change in weaning management on farm A (batches excluded from the study) had been planned for a prolonged period upon the advice of the veterinary consultant, thus not being the result of the study itself.

5.4.2 Data quality

Missing predictor variables on farms A and C were imputed using nearest neighbour imputation. Imputation of missing values on farm A was unlikely to introduce major bias since the prevalence of missing values in the final multiple regression model was low (5.0%). However, the final model on farm C may have been biased by imputation of missing values since the model included 'Growth rate WGT 2 to WGT 3', which was missing in 15.9% of the observations. Selected models were fitted to the non-imputed dataset and parameter estimates were compared with the imputed dataset to check for a hypothetical imputation bias. All parameters remained significant in both models (farms A and C) apart from the AR1 term on farm A (P = 0.13). In addition, fitting the model to the non-imputed datasets did not change the sign of any parameter estimates including the AR1 term on farm A. The first-order autoregressive term on farm A may have been subject to greater bias in the non-imputed dataset, since intermittent missing values in the time series affects the efficiency of parameter estimates for autoregressive terms. Since neither the significance nor the sign of parameter estimates changed for any of the other variables, imputation bias was not considered a major concern in either of the two datasets.

Unaccounted pigs may have biased either the outcome or the predictor variables, depending on the error source responsible for their occurrence. Unrecorded sale events bias 'Market weight' and 'Days to market'. In contrast, wrongly recorded pig numbers at all other production stages affect calculations of the 'Average pig inventory', thus causing bias in 'Mortality rate' and 'Feed intake'. We were predominantly concerned with unaccounted pigs due to unrecorded sales events, hence causing bias in the outcome variable. Unaccounted pigs at the finisher stage occurred at a relatively low frequency on all farms. Furthermore, the parameter 'Percentage of unaccounted pigs finisher stage' was not significant in any of the multivariable models. Hence, it appears that unaccounted pigs had no major effect on model estimates.

5.4.3 Carcass weight as outcome variable on farm A

Farm A did not record any pig live weights before transporting pigs to the abattoir. Routinely collected carcass weight records from the abattoir were used to assign the mean carcass weight of a marketing batch to the respective grower batch(es). This raises a problem, since carcass weight records did not distinguish between pigs sold from different age groups. Assigning the same mean marketing batch weight to different age groups may have introduced bias.

However, 57% of all marketing batches included only pigs from a single age group, hence not creating any bias in the outcome variable (Figure 4.1.11). From the remaining marketing batches, a median percentage of 89% of the batch came from the predominant age group. We argue that pigs sold from younger batches were likely to be the largest pigs of that batch, so that weight differences compared to pigs from older batches may have been small. Furthermore, the fact that the model resulted in high R-squared values (Regression R^2: 0.69; total R^2: 0.80) suggests that the use of carcass weight records of marketing batches did not present a major problem. However, improvement in data collection would imply to sell pigs from different age groups as separate lots or to obtain live weight records at the time of marketing.

5.5 Inferences to other study populations

The study population was a purposefully derived sub-sample of commercial New Zealand pig farms. Only producers who were (1) visited by the same veterinary consultant, (2) had an established grower herd monitoring system, and (3) were willing to participate in the study were included. Farm productivity and management on these farms may differ from those that do not use computerized production records. Therefore, selection bias may have been present in the study. However, we believe, that this analysis clearly showed the importance of monitoring and possible applications of deriving farm-specific models. Hence, if data of good quality are collected, explanatory models with good predictive value should be obtainable on other New Zealand farms.

Farms overseas slaughter pigs at greater live weights (Table 2.1.1). The growth curve of pigs between birth and maturity is of sigmoid shape (see p. 123). In New Zealand most pigs are marketed at around 90 kg live weight so that most of their growing period lies within the self-accelerating part of the growth curve. However, farms marketing pigs at greater live weights may need to include a quadratic effect of ‘Days to market’ to account for a decelerating growth rate near market weight. In our study, inclusion of the quadratic term of ‘Days to market’ did not reach significance in any of the final models.

Similar associations could be derived for factors associated with the performance of other farm animals than pigs. For instance, a farm-specific model predicting milk yield in dairy cows could be of great benefit to the producer. However, our analytical approach using an autoregressive model will not be appropriate if the observations are not equally spaced in time. For instance, a data set with milk parameters of individual dairy cows over several parities would require a different analytical approach. However, animal batches in poultry production present one possible application of our presented statistical technique.

5.6 Recommendations

5.6.1 Applicability of these models

Pork production is a business, which is predominantly concerned with maximizing profit and not pig performance. In fact, batches with highest market weights are rarely the best batches in terms of production efficiency and profitability. Hence, the models derived from this study are not meant to be used so that market weight can be maximized. However, the presented models allow forecasting batch market weight as a variable of ‘Days to market’ approximately one month prior to marketing. Whittemore (1993) stated “... most producers do face difficult marketing decisions at the point of sale of their product, and the outcome of those decisions has a dramatic effect upon the financial viability of the operation”. A batch of pigs has reached the optimum market weight range if the gain in revenue per pig for additional weight is no longer greater than the feed costs to put the additional weight on (Greenley 1997; Dritz et al. 1997a; Smith, J. H. 2003). Producers must constantly revise their decision what pigs to sell at what weight and to which market according to the time-changing behaviour of internal (e.g. farm constraints, pig performance) and external factors (e.g. season, feed and pig prices). The ability to forecast market weight a month prior to marketing presents a strong opportunity for pig producers to make and adjust their marketing decisions.

Furthermore, the models suggest that only few parameters need to be collected to predict 'Market weight', i.e. 'Weaning age', two 'Sample weights' and 'Days to market'. These parameters in addition to 'Season' and 'Finisher shed' produced reasonable estimates of batch market weight. This knowledge allows shifting the effort away from data collection towards data analysis and timelier decision-making.

Additionally, our results give a better understanding of how other production parameters change over time. This enables pig producers to evaluate their strengths and weaknesses throughout production. Based on this knowledge, producers and/or veterinary consultants can evaluate and apply management changes that are most effective in controlling and enhancing farm profitability whilst being associated with the lowest risk of failure.

5.6.2 Data collection

In our study, weight measurements played an important role in the prediction of 'Market weight'. Weight measurements are animal attributes, thus reflecting the animal's response to its environment. Particularly, sample weights taken prior to marketing are useful indicators of problems at specific production stages. We recommend weighing pigs at batch entry, at the start of the grower and finisher phase as well as at market. However, carcass weight data may replace pre-market live weight measurements if records allow distinguishing between pigs sold from different batches.

Producers often only weigh a sample of pigs to assess batch performance. However, the accuracy of sample weights depends on the sample size. Results from Schauer (2005a) suggest that at least half of the batch needs to be weighed following random sampling of pens to achieve a reasonable accuracy of more than 70%. Furthermore, consistent weighing and feeding times reduce variation in weight measurements due to variations in gut fill (Schauer et al. 2005b).

A decision also needs to be made whether to record individual pig weights or pen weights. While the former is more labour intense, it allows assessing weight variation. Variation between mean pen weights is not an appropriate measure of variation because the mean pen weight can result from various combinations of individual weights. However, weights of individual pigs within a pen are likely to be correlated (clustered data), so that weighing individual pigs from different pens would provide a more independent measure. Caldwell (1998) suggested a method of obtaining individual pig weights for growth curve measurements. He proposed to select randomly 20 pens and then one pig per pen. Each selected pig is ear-tagged and then weighed at each production stage. The advantage of this method is that 20 individual pig weights from different pens allow assessing variation in a group. However, moving one pig out of a group is usually more difficult than moving the whole pen.

Monitoring breeding herd data is essential in controlling entry parameters such as ‘Weaning age’ and ‘Entry numbers’. These parameters have a major influence on grower herd performance and farm profitability. Therefore, we strongly recommend keeping track of breeding herd records for problem detection and evaluation of intervention strategies.

Our study was unable to assess the feasibility of using feed intake data to predict market weight since only one farm had recorded feed intake data. However, monitoring feed intake and thus feed efficiency offers great benefits in production monitoring since feed costs present the greatest proportion of variable expenses.

Lastly, although financial data were not recorded in our study, collecting financial data will be essential to shift the focus from farm productivity to farm profitability, since this is the final aim of the pig unit.

Chapter 6 Conclusion

We were able to identify four production parameters (‘Weaning age’, two sample weights and ‘Days to market’) that were effective in predicting market weight on all three farms. In addition, we showed that regression analysis with autoregressive error correction is a useful modelling tool if both, predictor and outcome variables, include trend, seasonality and autocorrelation. Using an autoregressive model also has the advantage that future observations could be forecasted with accuracies greater than 70%. This is particularly useful as all predictor variables (apart from ‘Days to market’) could be obtained a month prior to marketing on all farms.

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